YRKESHÖGSKOLAN NOVIA

Optimizing Quality Control with AI-Powered Machine Vision in Manufacturing

A Study of Machine Vision Technology in Manufacturing

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Master's Thesis

Thesis for a Master of engineering (UAS) - degree

Degree Programme in Industrial Management and Engineering

Turku, 2025

MASTER THESIS

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Title: Optimizing Quality Control with AI-Powered Machine Vision in Manufacturing

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Date: 23.5.2025 Number of pages: 115 Appendices: 0

Abstract

This thesis addresses Valmet Automotive's Vehicle Contract Manufacturing business and investigates how modern quality control processes can be optimized using AI-powered machine vision systems. Although traditional quality control methods are dependable, they often fall short in meeting the high-speed and precision requirements of today's automotive production lines.

The study primarily explores the implementation of AI-based camera systems, with a specific focus on their deployment at the windshield inspection station. While machine vision tunnel systems are not yet in place at Valmet Automotive Plc, the research examines their feasibility through relevant industry case studies and theoretical insights. Using internal defect data from 2022 to 2024, quantitative data was collected and systematically analyzed to identify critical door-related defect trends. In parallel, an on-site empirical evaluation of the AI camera system was conducted, assessing its real-time functionality, operational performance, and financial implications. Additionally, qualitative methods including expert interviews and structured questionnaires with three external companies provided practical perspectives on the use, benefits, and challenges of machine vision systems.

The findings demonstrate that AI-driven machine vision leads to significant improvements in defect detection accuracy, production efficiency, and cost-effectiveness. These technologies reduce rework, enhance traceability, and enable real-time quality assurance on the production line. A detailed return-on-investment (ROI) analysis confirms the financial viability of such systems. This thesis provides Valmet Automotive Plc and the broader manufacturing industry with a strategic framework for integrating AI-based vision technologies to support efficient, scalable, and reliable quality control processes.

Language: English

Key Words: Quality Control in Automotive Manufacturing, Machine Vision Technology, Defect Detection

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1 Introduction

In the last decade, the growing demand for higher productivity and enhanced product quality has driven significant innovations, transforming traditional manufacturing into more advanced processes. Achieving higher productivity requires the detailed identification and elimination of non-value-added (NVA) activities, which can hinder efficiency (Judi et al., 2011; Smith & Brown, 2020). Among the critical stages of manufacturing, quality control plays a key role, utilizing various methods to ensure that each component meets strict quality standards (Green et al., 2021).

To address these challenges, the use of Artificial Intelligence (AI)-powered machine vision systems has emerged as a promising solution. These technologies enable real-time inspection, minimize human error, and support scalable quality assurance across various stages of the production line. At Valmet Automotive, growing interest in these systems led to a focused evaluation of AI-based cameras and the potential implementation of machine vision tunnel systems.

This thesis investigates the potential of AI-driven machine vision for optimizing quality control in vehicle manufacturing. While the original aim was to evaluate tunnel-based vision systems for door inspection, the lack of a physical installation during the thesis period shifted the practical focus toward the real-time performance of a standalone AI camera system used at the windshield inspection station. The study further incorporates quantitative defect data analysis, industry case studies, and expert feedback from questionnaires and interviews.

This introductory chapter presents the Research Background, Research Problem, Delimitations, and Structure of the Thesis.

1.1 Research Background

Valmet Automotive proposes a thesis dedicated to researching and developing the concept of a machine vision tunnel and AI cameras for quality control in manufacturing. This focused study explores the implementation of advanced technology as a practical solution to address quality assurance challenges.

In the automotive manufacturing industry, ensuring high-quality production is essential to guarantee safety, comply with strict regulatory standards, and maintain operational efficiency. Vehicle doors, as key components, require detailed inspections to ensure both functionality and aesthetic appeal. However, traditional quality control methods, such as manual inspections, are increasingly unable to meet the fast-paced demands of modern production lines. This limitation often leads to higher rates of undetected defects and inefficiencies in manufacturing processes.

The integration of machine vision technology with artificial intelligence (AI) provides an effective alternative to these outdated methods. This approach has demonstrated significant potential to improve manufacturing by increasing the precision and speed of defect detection, while also enhancing overall operational efficiency. Research has shown how these technologies can revolutionize quality control processes, creating new opportunities for smarter and more efficient manufacturing systems (Smith et al., 2020; Johnson & Lee, 2019).

In addition to the potential implementation of Vision Tunnel systems, Valmet Automotive is currently testing AI cameras on production lines. These cameras aim to improve defect detection efficiency and accuracy during assembly processes. This ongoing initiative reflects the company's commitment to leveraging AI in quality assurance.

1.2 Research Problem

Defects in vehicle doors such as surface scratches, misalignments, and structural weaknesses present considerable challenges for automotive manufacturers. These issues often result in costly rework during the finishing process or after-sales repairs, as well as potential reputational harm. Current quality control methods are labor-intensive, prone to human error, and frequently miss subtle or complex defects (Brown et al., 2021). These limitations highlight the need for an innovative solution like AI-enhanced Vision Tunnels, which offer real-time, accurate, and scalable quality control capabilities (Wang et al., 2022).

While detecting defects remains inherently reactive, integrating AI cameras into earlier stages of the production line enables faster identification and correction of issues before they escalate further downstream. Although this does not prevent defects from occurring, it significantly reduces the risk of costly rework and production delays, thereby supporting overall process reliability and efficiency (Zhang & Lee, 2023).Research Purpose, Guiding Questions, and Deliverables

This thesis investigates the feasibility and impact of integrating AI-powered machine vision systems into automotive manufacturing, with a primary focus on the inspection of car doors. While the implementation of Vision Tunnels remains a long-term goal, the study centers on the practical evaluation of an AI-based camera system currently operating at the windshield inspection station. By analyzing real-time performance data, internal defect statistics, and industry case studies, the research explores how AI camera systems and vision tunnel concepts can enhance quality control, streamline production processes, and support scalable automation strategies.

The research is guided by the following key questions:

1. What are the most frequent quality issues observed in vehicle doors at Valmet Automotive, and which of these can be targeted through machine vision systems?

2. How suitable is AI-based machine vision, particularly vision tunnels, for detecting door-related defects?

3. What is the potential operational and financial impact of deploying a machine vision tunnel at the door inspection station?

4. How does the AI-based camera system at the windshield station perform in terms of defect detection accuracy, operational efficiency, and technical limitations?

Deliverables

The outcomes of this thesis will include:

1. A classification and prioritization of door-related defects based on frequency, severity, and machine-vision detectability.

2. A case-based evaluation of vision tunnel systems for vehicle surface inspection, illustrating detection capabilities, inspection speed, and operational integration

3. An operational and financial feasibility study, including a 10-year ROI model, payback period, and savings estimation of implementing a vision tunnel system.

4. A focused case analysis of the AI camera project during the testing phase and at the windshield station, including its ROI, functionality, and documented constraints.

Table 1 illustrates the Research Questions, Deliverables, and Methods Used:

Table 1. Research Questions, Deliverables, and Methods used

Research Question	Deliverable	Method(s) Used
1. What are the most frequent quality issues observed in vehicle doors at Valmet Automotive, and which of these can be targeted through machine vision systems?	1. Classification and prioritization of door-related defects based on frequency, severity, and machine-vision detectability.	Quantitative analysis of internal Power BI defect data (2022–2024), classification by type and error class, machine vision relevance mapping.
2. How suitable is AI-based machine vision, particularly vision tunnels, for detecting door-related defects?	2. A case-based evaluation of vision tunnel systems for vehicle surface inspection, illustrating detection capabilities, inspection speed, and operational integration	Literature review (case studies from Volvo and safety glass inspection), defect-type detection feasibility analysis, technology–defect mapping, and insights from expert questionnaires/interviews.
3. What is the potential operational and financial impact of deploying a machine vision tunnel at the door inspection station?	3. Operational and financial feasibility study, including 10-year ROI model, payback period, and savings estimation of implementing a vision tunnel system.	Cost-benefit analysis based on defect repair time, labor rates, and investment cost, ROI calculation, Excel-based financial modeling.
4. How does the AI-based camera system at the windshield station perform in terms of defect detection accuracy, operational efficiency, and technical limitations?	4. A focused case analysis of the AI camera project during the testing phase and at the windshield station, including its ROI, functionality, and documented constraints.	On-site functional analysis and process documentation, evaluation of performance based on internal feedback and detected defect types, ROI calculation, identification of environmental and training limitations.

This thesis uses a mixed-methods approach combining quantitative and qualitative methods. Internal defect data from Valmet Automotive (2022–2024) was analyzed to identify and classify door-related quality issues detectable by machine vision. Literature reviews and two questionnaires plus one interview with industry experts supported the evaluation of vision tunnel technologies. A financial feasibility analysis including ROI and payback modeling was conducted for potential system investment. Additionally, an empirical on-site study of the AI camera at the windshield station assessed real-time performance, technical constraints, and cost-effectiveness. This comprehensive approach ensured practical relevance and theoretical grounding. Supporting this multi-method approach were internal documents, instructional materials, operator feedback, and recent literature. This ensured that the study remained both academically grounded and practically aligned with current industrial challenges.

1.3 Delimitations

This thesis is delimited to the inspection of vehicle doors and the body area before the windshield is glued onto the vehicle frame at Valmet Automotive. While the original main objective was the evaluation and potential implementation of a machine vision tunnel system for door inspection, this specific project was not realized during the active thesis period. As a result, the research scope was expanded to include a detailed evaluation of the AI-powered camera system currently in operation at the windshield inspection station. This system provided a valuable real-time experience and served as a practical reference point to complement theoretical insights, external case studies, and the findings from questionnaires and interviews with industry professionals.

The focus of this thesis remains on AI-powered visual quality inspection, specifically targeting surface-level defects such as scratches, dents, paint damage, and misalignments. Although door assemblies include mechanical and electrical components, such as wiring harnesses and locking mechanisms, this study does not cover functional testing or verification of these internal systems. The analysis is strictly limited to visual defect detection and excludes areas such as mechanical durability testing or electronic diagnostics.

Due to the absence of a machine vision tunnel system at the site, insights related to such systems are derived from literature reviews and selected case studies, most notably the Atlas system implemented by Volvo Cars. Therefore, conclusions regarding tunnel-based systems are theoretical and based on documented external experiences rather than direct implementation. However, the AI camera installed at the windshield inspection station provided a valuable real-time experience during the thesis work. As a machine vision solution, it shares core functionalities with tunnel-based systems, such as defect detection, image processing, and automated feedback. The primary distinction lies in the configuration: while the AI camera operates as a standalone unit, vision tunnel systems typically consist of multiple synchronized cameras embedded within a tunnel structure to enable full-surface inspection. This hands-on experience with the AI camera supported a practical understanding of machine vision technology and contributed significantly to the research findings.

Confidential internal data from Valmet Automotive, particularly related to defect statistics and ROI calculations, has been handled in accordance with university policy. A redacted version of the thesis will be made publicly accessible, while a full version will remain confidential and archived according to academic and organizational guidelines.

Lastly, financial calculations and defect classifications are based on internal PowerBI data covering the years 2022 to 2024, along with assumptions and benchmarks consistent with industry standards. These findings are therefore limited to the defined production environment and timeframe.

1.4 Structure of the Thesis

This thesis is structured into six main chapters, each of which contributes to addressing the research objectives and answering the defined research questions:

Chapter 1: The introduction chapter outlines the research background, objectives, research problem, and questions. It also defines the study’s scope and delimitations.

Chapter 2: Valmet Automotive Plc The company background chapter presents an overview of Valmet Automotive Plc.

Chapter 3: Methodology describes the research approach and data collection methods used in the study. It includes literature review, quantitative defect analysis, case evaluations, financial modeling, and expert feedback gathered through interviews and questionnaires.

Chapter 4: Theoretical Background reflects on various academic and industry perspectives related to quality management, machine vision systems, and relevant case studies.

Chapter 5: Findings and Analysis presents the results of the internal data assessment, AI camera evaluation, and case-based analysis of machine vision systems, and expert feedback gathered through interviews and questionnaires.

Chapter 6: Conclusion summarizes the key findings, evaluates the return on investment, discusses the practical implications of AI-powered quality control, and suggests future research directions.

2 Valmet Automotive Plc

This thesis will address information related to Valmet Automotive's Vehicle Contract Manufacturing (VCM) business. Valmet Automotive Plc is a leading European company specializing in vehicle manufacturing, electric vehicle (EV) battery systems, and automotive components. With gross sales amounting to EUR 2,3 billion (net sales EUR 511,4 million), Valmet Automotive has positioned itself as a key player in the global automotive industry. The company employs over 3,200 employees (Valmet Automotive 2025).

Established in 1968, the company has grown into one of the largest contract vehicle manufacturers globally, with over 1.8 million vehicles produced at its Uusikaupunki plant in Finland. Valmet Automotive's operations are divided into three business lines: Vehicle Contract Manufacturing (VCM), Roof & Kinematic Systems (RKS), and Electric Vehicle Systems (EVS). The company operates production facilities in Finland, Germany, and Poland, serving renowned OEMs such as Mercedes-Benz, Porsche, Saab, and Fisker (Valmet Automotive 2023).

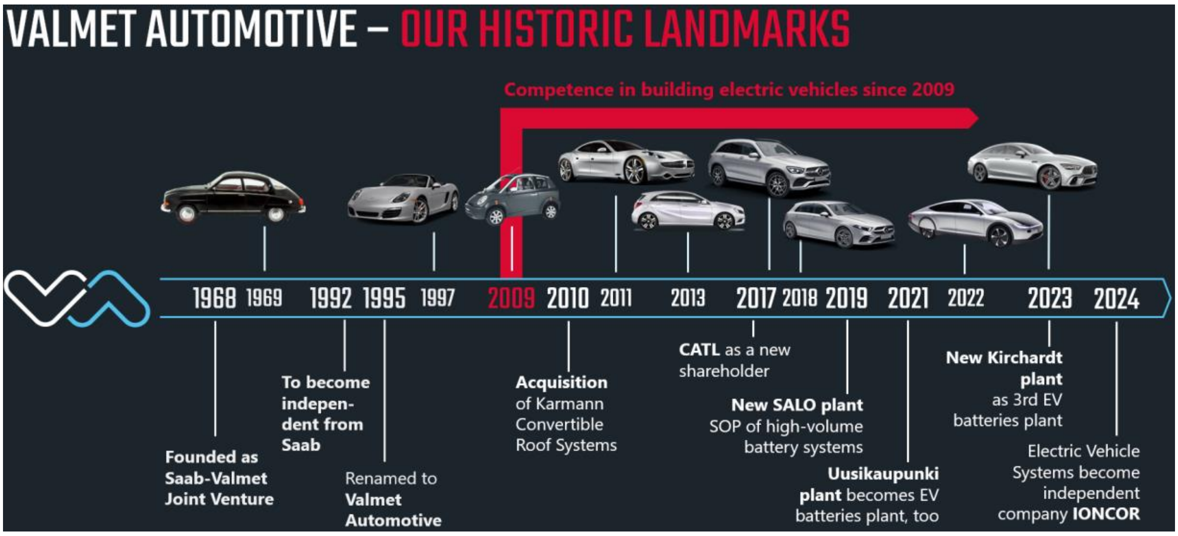


Figure 1: Valmet Automotive's historic landmarks (Valmet Automotive 2024).

Valmet Automotive is recognized for its expertise in advanced automotive solutions, including convertible roof systems, electric vehicle charging flaps, and active spoilers. Its commitment to innovation and high-quality manufacturing has made it a trusted partner for global car brands. In addition, the company achieved CO_2-neutral certification for its operations in 2022, highlighting its dedication to sustainability (Valmet Automotive 2023).

In 2024, Valmet Automotive restructured its battery business under the new name IONCOR, which continues the development and production of battery systems for electrified vehicles. Operating independently, IONCOR leverages the expertise gained under Valmet Automotive to expand its offerings across automotive and non-automotive sectors, supporting the global shift toward decarbonization (Valmet Automotive 2023).

3 Methodology

This chapter outlines the methodological approach adopted in this thesis, which aims at optimizing quality control through the implementation of AI-powered machine vision systems at Valmet Automotive. The methodological choices reflect the research questions and deliverables established at the beginning of this thesis. Initially, the topic was intended to focus on a specific machine vision tunnel project, however, due to delays in the implementation timeline, the project did not proceed during the active writing period. Therefore, based on the guidance of my supervisor, the focus was redirected toward the theoretical foundation of machine vision technologies and the evaluation of the ongoing AI camera project at Valmet Automotive, which provided a more practical and timely case for analysis.

3.1 Literature review

A structured literature review was conducted to establish a solid theoretical foundation for this thesis. The selected sources were evaluated based on their relevance to the automotive industry, current developments in machine vision technologies, and established principles in quality management. Additionally, attention was given to the applicability of AI-powered machine vision systems beyond the automotive sector, especially regarding their role in defect detection in other manufacturing industries. The review also explored connections to the cost of quality framework and examined how such technologies contribute to efficiency improvements across sectors. To complement academic literature, practical materials such as technical manuals, training videos, and manufacturer documentation were also included, offering insight into real-world implementation and system functionality. The selection criteria included:

- Academic articles and books published primarily within the past decade.
- Industry reports and case studies relevant to automotive manufacturing, machine vision, and AI implementation.
- Publications providing foundational theories on quality management and quality cost analysis.

Exclusion criteria were also clearly defined to maintain focus and relevance. These included:

- Sources older than ten years, except seminal works that significantly influenced current theories or practices.

- Literature primarily addressing machine vision applications outside manufacturing contexts or without direct implications for automotive quality control.
- Materials lacking scientific credibility, practical relevance, or direct applicability to industrial-scale manufacturing environments.

Additionally, non-academic practical materials, such as technical manuals, instructional videos, manufacturer documentation, and industry expert articles, were included selectively to offer insights into practical system implementations, operational challenges, and technological functionalities. The defined exclusion criteria ensured the literature remained current, scientifically robust, and directly applicable to industrial-scale automotive quality control.

Due to the confidentiality typical of automotive manufacturers, acquiring relevant automotive-specific case studies proved challenging, limiting direct access to comprehensive practical examples. Consequently, research relied significantly on academic journals accessible via Novia's online library and Google Scholar.

The purpose of this rigorous approach to source selection was to thoroughly identify and synthesize existing knowledge, pinpoint current technological advancements, recognize potential limitations, and explore practical implications of AI-enhanced vision systems. This structured methodology ensured comprehensive coverage and relevant insights applicable to manufacturing environments, particularly aligning with the operational context of Valmet Automotive.

3.2 Quantitative Defect Data Analysis

Quantitative data was collected and systematically analyzed to address the research question regarding the most frequent and critical quality issues observed in vehicle doors. The objective of this analysis was to establish a factual and measurable foundation to evaluate the potential of AI-powered machine vision systems in improving quality control outcomes.

To analyze the distribution and impact of door-related quality issues at Valmet Automotive, including all relevant models (Product 1 and Product 2), a meeting was conducted with the

Senior Quality Engineer from the Production department. During this meeting, I requested historical defect data for both models. The Senior Quality Engineer provided comprehensive defect records in form of Pareto charts covering the past three years, before 3 years period were different products.

I was able to make the analysis based on the provided Four Pareto charts. The analysis specifically investigated which defect types could be reliably detected or influenced by machine vision systems, and to what extent artificial intelligence (AI) can handle the identified quality challenges. A Pareto analysis was conducted using defect data extracted from PowerBI, covering a three-year period between 2022 and 2024.

The analysis involved the following steps:

- Data collection: Historical defect records were extracted from Valmet Automotive's internal PowerBI database, encompassing a three-year period from 2022 to 2024. The dataset included detailed information on defect types, repair times, and defect classifications, specifically focusing on door-related quality issues. Initially, data from three production units was available, however, one unit was excluded as it is no longer produced at Valmet Automotive, ensuring only current production units were analyzed.

- Data structuring and classification: The raw data was categorized according to defect types (e.g., mechanical damage, surface defects, misalignment) and linked to associated corrective measures. Each entry was evaluated for frequency and repair duration, enabling the identification of recurring patterns.

- Statistical analysis: A detailed quantitative assessment was performed, including frequency distribution analysis, mean repair time calculations, and identification of high-impact defect categories. This statistical evaluation helped to determine which defect types represented the greatest burden in terms of both occurrence and required repair effort.

This data-driven approach provided a reliable basis for prioritizing defect categories that could potentially benefit from machine vision-based detection and documentation. By identifying the most frequent and time-consuming defect types, the analysis supports targeted recommendations for implementing AI vision systems where they are likely to yield the highest operational and economic benefits. Defects with repair times under ten minutes were not considered, as they are typically reworked immediately on the production line. Only defects requiring more than ten minutes of repair time those reworked in the finishing line were included in the analysis, as these incur significantly higher labor and process costs, making them ideal targets for automation through AI-based inspection systems.

3.3 Case Study Evaluation

In order to understand the practical implications of AI-powered machine vision systems and to benchmark industry practices, two case studies were selected and critically evaluated. Initially, 13 potential case studies were identified and reviewed. Many of these cases were deeply technical, focusing extensively on AI functionalities, or were relevant to industries other than automotive manufacturing. Several cases lacked detailed quantitative data or specific information relevant to automotive applications, primarily due to industry confidentiality and competitive sensitivities. These Two cases served as reference points to assess how similar technologies have been implemented in industrial settings, with particular attention to effectiveness, challenges, and integration strategies. However, it is important to note that identifying suitable case studies within the automotive sector proved challenging. Due to the highly competitive nature of the industry and the sensitivity surrounding proprietary production technologies, most automotive companies are reluctant to share detailed information about their machine vision systems or quality control processes. As a result, publicly available and well-documented case studies from this domain remain limited. Despite these constraints, two relevant and technically insightful cases were identified and examined.

- Atlas Inspection System (Volvo Cars): This case was selected due to its direct relevance to the automotive manufacturing context. It offered comprehensive documentation of the implementation of an automated surface inspection system, including data on detection accuracy, inspection speed, and its influence on operational efficiency. The case was particularly useful in illustrating how large-scale OEMs integrate machine vision into complex production environments.

- AI-Based Online Detection of Edge Defects: This case study was chosen for its technical depth and relevance to defect detection in manufacturing processes. It focused on the integration of AI algorithms for real-time identification of edge defects and provided valuable insight into system architecture, data processing requirements, and the limitations encountered in live production settings.

Both case studies were analyzed through a comparative lens, with the aim of extracting practical lessons that could inform Valmet Automotive's approach to implementing similar technologies. The evaluation considered aspects such as system performance, integration challenges, data handling, and return on investment. The insights derived from these cases were then contextualized within the specific production environment at Valmet Automotive, contributing to a more grounded and actionable understanding of the potential benefits and barriers associated with AI-based defect detection systems.

3.4 Financial and Operational Feasibility Study

To evaluate the financial and operational viability of implementing a machine vision tunnel system, a comprehensive feasibility study was conducted. This approach was chosen because it effectively integrates quantitative financial analysis with operational insights, providing a robust basis for strategic investment decisions. Alternative methods such as basic payback calculations or qualitative evaluations were considered less suitable because they do not fully address the complexity and detailed financial implications of technological upgrades.

The feasibility study involved a detailed Return on Investment (ROI) analysis, structured around the following key components:

- Estimation of Initial Investment Costs: Detailed cost estimates were gathered, covering the capital expenditure(CapEx), installation, calibration, training, and initial setup. These were derived from industry benchmarks, vendor quotations, and internal estimates provided by Valmet Automotive's engineering team.

- Operational Cost Assessment: Operational and maintenance costs were assessed, although annual maintenance and operational costs were excluded in this analysis due to unavailable specific data. Future studies should consider these additional costs for a more comprehensive analysis.

- Modeling Potential Savings: Savings were projected based on anticipated reductions in defect rates and associated repair times. A conservative defect reduction estimate, drawn from industry benchmarks such as the Volvo Atlas case study, was used to calculate expected savings. The labor costs for repairs were quantified based on standard industry labor rates and historical repair times. The analysis consequently estimated annual gross savings resulting from the implementation of the machine vision tunnel.

- Sensitivity Analysis: The ROI analysis considered variations in defect reduction rates, possible fluctuations in production volume, and maintenance expenses. This sensitivity analysis provided insights into the financial model's robustness under different operational scenarios.

- Evaluation Period: A 10-year operational period was selected to align with the typical lifecycle of industrial inspection equipment, allowing for both immediate financial implications and cumulative long-term benefits to be clearly represented.

By comprehensivley integrating quantitative cost-benefit analysis with Valmet Automotive's operational realities, this feasibility study offers valuable insights for strategic decision-making regarding AI-powered machine vision systems. It highlights both the economic potential and the limitations based on current production volumes, enabling informed decisions about future technology implementations.

3.5 On-site AI Camera Analysis

As part of the methodological approach, an in-depth on-site empirical evaluation was conducted to assess the performance and practical relevance of an existing AI-powered camera system currently implemented at Valmet Automotive’s windshield inspection station. The inclusion of this AI camera system in the research was due to the vision tunnel project not taking place during the thesis timeframe. After discussing the matter with the thesis supervisor, the decision was made to explore the AI camera as an alternative, providing a relevant real-time case study.

The on-site evaluation encompassed several key activities:

- Initial Coordination and Access: Communication was established with the Project Engineer in charge of the AI camera pilot project. After obtaining approval, attendance at the camera testing phases in the innovation center and later observations on the actual production line were organized.

- Direct Observation and Documentation: Active participation included observing the system's installation, initial setup, and testing in the innovation center. Detailed notes were taken on the camera's operational procedures, adjustments, and interactions with technicians and engineers during the calibration and testing phases.

- Real-time Production Line Monitoring: Observations and documentation extended to the production line environment. The camera's real-time defect detection capabilities were monitored during regular production shifts, focusing on its effectiveness, speed, accuracy, and integration into the production workflow.

- Photographic Documentation: Photographs were taken both by the author and provided by the Project Engineer to thoroughly document the AI camera system in both testing and operational environments. These images served to visually validate observations and support the analysis.

- Performance and Constraint Analysis: The camera's operational effectiveness under production conditions was critically assessed. Specific attention was paid to environmental challenges such as lighting variations, reflection issues, positional variability, and vibrations that might affect detection accuracy. This phase of analysis also identified practical limitations and potential areas for improvement.

- ROI Evaluation: An ROI analysis for the AI camera was conducted based on actual defect detection outcomes, repair time data, and labor costs. This provided an economic evaluation of the system's impact and validated its financial feasibility within real-world operational conditions.

This comprehensive, first-hand analysis provided crucial insights into the performance and real-world applicability of AI-based machine vision technology within Valmet Automotive. The hands-on involvement enriched the authenticity and depth of the research, enabling robust conclusions and practical recommendations for future technology implementation.

3.6 Questionnaires and Interviews

To supplement quantitative analysis and case study evaluations, qualitative methods involving two structured questionnaires and one semi-structured interview were conducted. The objective was to validate findings and gain practical industry perspectives on adopting, operating, and the impact of AI-powered machine vision systems. Due to confidentiality constraints in the automotive industry, obtaining responses was challenging. Initially, responses were requested from three automotive companies, however, only one automotive manufacturer responded positively. Consequently, to fulfill the planned qualitative analysis, additional participants from closely related manufacturing industries were included. Participants included:

- One vehicle manufacturer (customer, anonymized due to confidentiality)
- One battery module manufacturer (supplier, anonymized due to confidentiality)
- One wire harness production company (supplier, anonymized due to confidentiality)

Participants were chosen based on their expertise and direct involvement with machine vision technologies, ensuring relevant and diverse insights. These individuals were identified through personal industry contacts, emphasizing their specific roles in implementing or managing machine vision systems. The questionnaire and interview questions were specifically designed to explore practical challenges, operational effectiveness, and financial aspects, aiming to understand diverse industry applications and cross-sectoral insights. Although limited, these qualitative inputs provided critical real-world validation of theoretical and quantitative analyses, highlighting both successful practices and common challenges. This qualitative approach deepened the thesis by capturing detailed experiences from multiple stages within automotive and related manufacturing sectors, thereby informing practical recommendations for Valmet Automotive and similar industrial environments.

Interview Questionnaire: AI and Machine Vision in Defect Detection

I am writing my thesis about “Optimizing Quality Control with AI-Powered Machine Vision in Manufacturing” for Valmet Automotive. I would be very grateful if you could answer the following 10 questions based on your experience with machine vision systems.

1. Could you briefly introduce your role and responsibilities within the company?

2. What type of machine vision technology is implemented at your facility (e.g., 2D/3D camera, AI-based vision, classical rule-based vision)?

3. For which components or areas is the machine vision system primarily used to detect defects? (e.g., doors, windshields, body panels).

4. What types of defects is the system particularly effective in detecting? Could you provide examples?

5. What are the main benefits you have observed since implementing the system (e.g., accuracy, speed, reduced rework, traceability)?

6. Have you identified any limitations or challenges with the system (e.g., environmental conditions, detection of certain defect types, integration with existing processes)?

7. Can you share how you calculated or evaluated the Return on Investment (ROI) for the system?

8. What are the typical annual maintenance or operational costs associated with the system (e.g., calibration, spare parts, licenses)?

9. From your experience, how accurate and reliable is the system in comparison to manual inspection? Have you conducted any internal benchmarking?

10. Based on your experience, would you recommend this technology to other manufacturers? What would be your key advice for successful implementation?

Thank you

The questionnaire and interview consisted of ten questions designed specifically to address the technical, operational, and financial aspects of machine vision system implementation. These questions were chosen to extract detailed information on the type and effectiveness of machine vision technologies used, their observed benefits and limitations, financial evaluation methods, maintenance practices, and overall reliability compared to manual inspection methods.

The structured questions aimed at:

- Understanding roles and responsibilities to contextualize responses
- Identifying the specific type of machine vision technologies implemented
- Pinpointing specific components or areas where machine vision systems are most effective
- Highlighting typical defects detected and system efficiency in defect detection
- Evaluating observed operational benefits such as accuracy, speed, and traceability
- Identifying encountered limitations or environmental challenges
- Assessing financial evaluations, specifically the calculation of return on investment (ROI)
- Gathering information on annual operational costs
- Comparing system accuracy and reliability against manual inspections, and understanding internal benchmarking practices
- Collecting recommendations and practical advice based on the participants' experiences

These questions were deliberately structured to cover multiple perspectives, such as operational effectiveness, technical challenges, and financial justification, ensuring comprehensive qualitative data. However, reflecting on the feedback, potential additional questions could have addressed more deeply aspects of environmental adaptability, integration complexity with existing processes, and potential strategies for overcoming identified limitations.

Responses revealed differences based on industry-specific practices and highlighted common benefits, such as improved accuracy and reduced rework, while also noting challenges including sensitivity to environmental conditions and initial integration complexities. The responses provided valuable real-world validation for theoretical assumptions and quantitative findings presented in this thesis, thus enriching the research by integrating diverse industrial experiences from multiple manufacturing contexts.

4 Theoretical Background

This chapter provides the conceptual and technological foundation needed to support the research. It begins by outlining the principles of quality management and continues with a discussion of quality control practices specific to the automotive industry. This is essential for understanding the operational environment in which inspection systems function.

To highlight the economic implications, quality-related costs are also examined, with emphasis on how delayed defect detection impacts rework and failure costs. The chapter then contrasts manual visual inspection with machine vision, offering a comparative perspective on reliability, scalability, and performance.

Finally, the chapter explores the technical fundamentals of machine vision, artificial intelligence, and their combined role in enhancing automated quality control processes. The focus is placed on how these technologies are applied within manufacturing, with specific relevance to automotive production.

This structure was selected to connect traditional quality theories with advanced digital inspection technologies, enabling a comprehensive understanding of the challenges and opportunities in implementing AI-based quality control systems.

4.1 Quality Management

Quality management (QM) represents an organizational approach aimed at ensuring that products and services constantly meet or surpass customer expectations through systematic methods of control, assurance, planning, and continuous improvement (Juran & Gryna, 2021; Oakland, 2020). Central to QM are principles such as prioritizing customer needs or requirements, involving leadership, managing processes effectively, and making updated, data-driven decisions. Together, these principles create a strategic foundation steering organizational activities toward achieving predefined quality standards (Goetsch & Davis, 2021). It is important to recognize that quality expectations differ across sectors, for instance, in automotive manufacturing, the emphasis is on reliability and defect-free products, whereas healthcare services prioritize accuracy, promptness, and patient confidentiality (Nenadál et al., 2018). Nevertheless these differences, quality is constantly seen as a measurable feature shaping customer satisfaction, employee engagement, productivity, profitability, and competitive advantage. International standards, such as ISO 9001:2016 and IATF 16949, are particularly significant in the automotive industry, setting clear expectations for original equipment manufacturers (OEMs) and suppliers, thus highlighting QM’s vital role in sustaining long-term business success (Oakland, 2020).

4.2 Quality Control in Automotive Manufacturing

Quality control (QC) in automotive manufacturing involves specific practices and tools designed to systematically detect, monitor, and correct defects during vehicle production. The primary goal is ensuring each vehicle precisely meets the industry's strict quality requirements and aligns closely with customer expectations (Juran & Gryna, 2021; Oakland, 2003). Automotive QC contains a range of approaches, For example, the DMAIC (Define, Measure, Analyze, Improve, Control) methodology is commonly used within automotive manufacturing as a structured approach to improve quality. DMAIC is part of the broader Lean Six Sigma practices, which combine statistical quality control with lean manufacturing principles originally developed by Toyota during the 1950s to eliminate waste and optimize processes. This approach has proven effective in systematically identifying and addressing production defects. For instance, Hidayat et al. (2024) applied the DMAIC methodology in a study targeting defects such as monoiri, misrun, and coating loss in piston manufacturing. Utilizing analytical tools such as Pareto diagrams and fishbone diagrams, the study pinpointed root causes primarily linked to material, machine, and environmental conditions. Implementation of targeted measures, including monitoring procedures and scheduled maintenance and cleaning routines, led to big improvements in defect reduction and overall process reliability.

The fundamental Statistical Process Control (SPC), where control charts are used to identify and eliminate process variations, serves as the basis for ensuring stable and predictable production processes. This technique plays a crucial role in reducing the occurrence of defects. More advanced methodologies such as Design of Experiments (DoE), Taguchi methods, and Failure Mode and Effects Analysis (FMEA) further support process optimization. These methods aim to improve product robustness and reliability, however, their implementation can be limited by complexity and the requirement for specialized statistical expertise (Antony & Kaye, 1995; Antony et al., 1998). It is important to note that Six Sigma is not a single technique but rather a comprehensive methodology that encompasses a structured set of tools and practices including SPC, DoE, and FMEA to systematically identify, measure, and eliminate sources of variation in production processes. Six Sigma methodologies are increasingly implemented by automotive manufacturers to minimize defects through ongoing process improvements, significantly boosting product quality and operational efficiency (Breyfogle & Cupello, 2001; Mahanti &

Antony, 2005). FMEA, specifically, serves as a critical tool in proactively identifying potential defects or failures in the design and manufacturing processes, allowing manufacturers to prioritize risks and implement corrective measures efficiently (Xie & Goh, 1999; Dale et al., 2003). Additionally, acceptance sampling methods are widely employed within automotive production, allowing manufacturers to efficiently assess the quality of component batches or completed vehicles by inspecting representative samples, thus balancing inspection effectiveness with productivity (Gardiner & Mitra, 1994; Slattery, 2005).

4.3 Quality costs

Quality costs, often referred to as the Cost of Quality (COQ), represent all expenses an organization encounters in ensuring products or services meet defined quality standards and customer expectations. Managing these costs effectively enhances customer satisfaction, reduces operational risks, and increases substantial value to the organization.

One of the most recognized models for categorizing quality-related costs is the Prevention-Appraisal-Failure (P-A-F) model, initially developed by Armand Feigenbaum in 1956. This model classifies quality costs into three distinct categories: prevention, appraisal, and failure costs (Rosiawan et al., 2019), as illustrated in Figure 2.

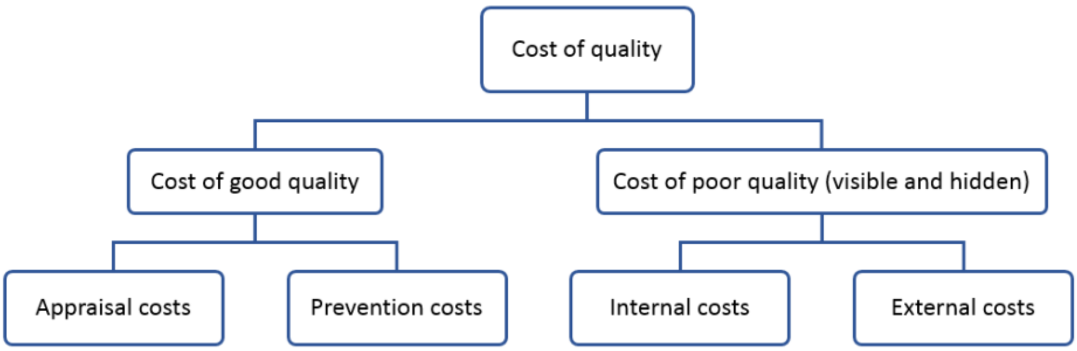


Figure 2. Quality costs. Adapted from Juran and Godfrey (1998, 8.4-8.8)

- Appraisal Costs: Appraisal costs happen from activities aimed at evaluating and inspecting products or services to ensure they meet proved quality standards. This category involves incoming material inspections, in-process and final product inspections, calibration of measurement equipment, and comprehensive quality audits. While appraisal costs are necessary, excessively high appraisal expenses often signal inefficiencies within the production processes, highlighting areas requiring attention and improvement (Wood, 2012).

- Prevention Costs: Prevention costs involve proactive measures designed to prevent defects from happening in the first place. They include activities such as quality planning, employee training, supplier assessments, quality audits, and establishing robust quality management systems. Investing strategically in prevention not only significantly reduces defects and production inefficiencies but also contributes to substantial long-term savings (Wood, 2012).

- Internal Failure Costs: Internal failure costs are encountered due to defects identified before products are delivered to customers. Such costs include expenses related to rework, scrap, waste, downtime, and associated inefficiencies. Effective management of internal failure costs can significantly improve operational efficiency, reduce waste, and improve overall production effectiveness, thus positively impacting profitability (Wood, 2012).

- External Failure Costs: External failure costs occur when defective products reach customers, potentially leading to warranty claims, product returns, replacements, repairs, customer dissatisfaction, and damage to organizational reputation. Managing and minimizing external failure costs is crucial for maintaining customer loyalty, preserving brand reputation, and sustaining long-term business success (Wood, 2012).

According to The National Highway Traffic Safety Administration (NHTSA) below in figure 3, indicates key statistics regarding vehicle manufacturing and recalls in 2022, 81 million vehicles were produced globally in 2022, Of these, 25 million units were affected by recalls, highlighting substantial quality concerns within the automotive manufacturing sector.

MANUFACTURER	Number of Recalls	Percent of Total	Affected vehicles
[illegible]	67	17%	8,636,265
[illegible]	45	11%	1,040,885
[illegible]	42	11%	273,286
[illegible]	38	10%	3,041,431
[illegible]	35	9%	203,694
[illegible]	33	8%	969,993
[illegible]	32	8%	3,371,302
[illegible]	24	6%	1,458,962
[illegible]	22	6%	1,452,101
[illegible]	22	6%	105,880
[illegible]	20	5%	3,769,581
[illegible]	19	5%	1,000,455

Figure 3. Recalls in 2022, from 1 January to 19 December (NHTSA, 2023)

Quality Costs as a Function of Detection Point

According to (Maximl 2021), the 1-10-100 rule illustrates the escalating costs associated with correcting errors as they progress through different stages of the production and customer-service process. This rule highlights that preventing errors at the earliest possible stage is significantly more cost-effective compared to addressing them later.

This rule strongly emphasizes the importance of investing in proactive quality management practices rather than reactive solutions, enabling companies to preserve resources, sustain customer satisfaction, and maintain competitiveness in the marketplace.

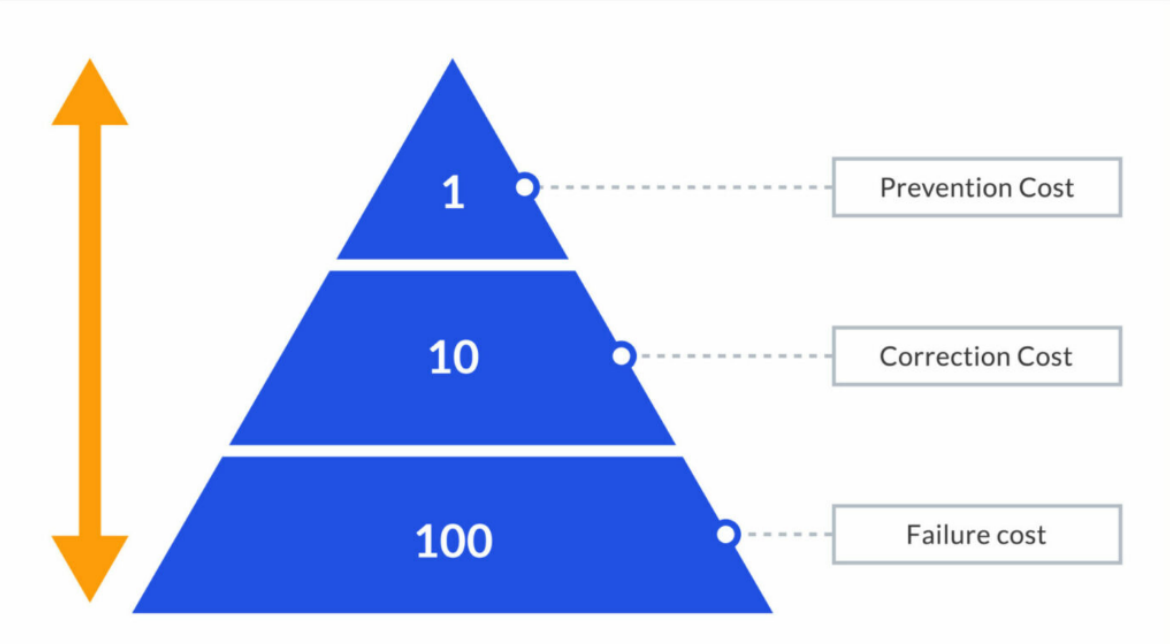


Figure 4. 1-10-100 Rule Example (Maximl 2021)

The cost of correcting an error increases exponentially the later it is detected in the production process. For example, if identifying and resolving a defect before production costs $1, the same issue may incur a cost of approximately $10 during production. Should the defect remain undetected until after production, the cost can escalate to $100. This highlights the importance of early detection and prevention in maintaining cost efficiency and product quality throughout the manufacturing cycle.

The 1–10–100 Rule: How the Timing of Defect Detection Impacts Manufacturing Costs Across the Supply Chain

The “1” – Pre-Production Stage

In the pre-production phase, manufacturing activities are primarily focused on product development and the inspection of incoming raw materials. Identifying a defect at this stage typically has a minimal financial impact on the organization. Design-related errors can be rectified through revisions to technical drawings or by engaging external expertise. Similarly, if raw materials are found to be non-compliant, the production timeline may experience delays, however, the associated costs and responsibilities for replacement generally fall under the purview of the supplier (Maximl, 2021).

Therefore, early-stage defect detection is relatively inexpensive and has limited influence on the company's revenue. Moreover, rigorous inspections conducted at this stage enhance the reliability of materials used in production and can support higher productivity levels without compromising quality.

The "10" – Production Stage

The cost implications of identifying defects during the production stage vary depending on the timing and severity of the issue. In the early stages of production, the manufacturer, having already accepted the raw materials, assumes responsibility for any quality issues that arise. This may involve significant logistical challenges and financial burdens associated with reordering inventory or adjusting production schedules (Maximl, 2021).

When defects are detected at later stages of production, the organization incurs both corrective and preventive costs. Corrective costs may include reworking defective units, conducting root cause analysis, or producing new components. Preventive costs arise from implementing new systems or controls to minimize the recurrence of similar defects.

In addition to these direct costs, the organization may experience resource wastage and delays in fulfilling customer orders. These disruptions can adversely affect customer satisfaction and the company's reputation.

The "100" – Post-Production Stage

Detecting defects after production has been completed particularly during final inspection or once the product is already in the market can lead to significant financial and reputational damage. If a product fails pre-shipment inspection, the manufacturer must urgently identify the root cause. This investigation may be complex and time-consuming, especially in the absence of robust internal traceability systems. Additionally, defective products must be reworked or scrapped, leading to increased operational overhead and lost production time (Maximl, 2021). Figure 4. describes all these last 3 headings.

If defects are only discovered once the product has reached customers, the consequences are considerably more severe. The company may be required to issue recalls, cover warranty costs, handle litigation, and invest in public relations efforts to manage brand perception. In the event that a defect causes harm or loss to end users, the damage to the company's reputation can be long-lasting or even irreversible. Given the speed at which information circulates today, such incidents can quickly become public knowledge, potentially resulting in a loss of market trust and competitive standing.

According to (Wood, 2012) the following figure 5. Successful management of quality costs depend much on the timely detection of defects during the production and delivery processes. The relationship between the detection point of a defect and its related cost is explained clearly in Figure 5. This graph highlights the critical importance of early defect detection, indicating that the cost of addressing quality issues increases dramatically the later in the production cycle these issues are identified.

At the earliest stages such as prevention activities and component inspections the costs related to managing quality defects stay comparatively low. As the product moves forward in the production cycle, transitioning through subsystem assembly, final inspection, and shipping stages, the financial impact of correcting defects escalates significantly. Further delays in defect detection, resulting in field repairs, field failures, or litigation, can lead to significant and potentially catastrophic financial and reputational consequences for the organization.

The data utilized to establish such a quality cost measurement framework should come from various reliable sources, including inspections, tests, process control measurements, evaluations, quality audits, and customer complaints. Implementing a robust and reliable quality cost measurement system enables organizations to identify, prioritize, and address performance weaknesses and potential cost-reduction opportunities successfully.

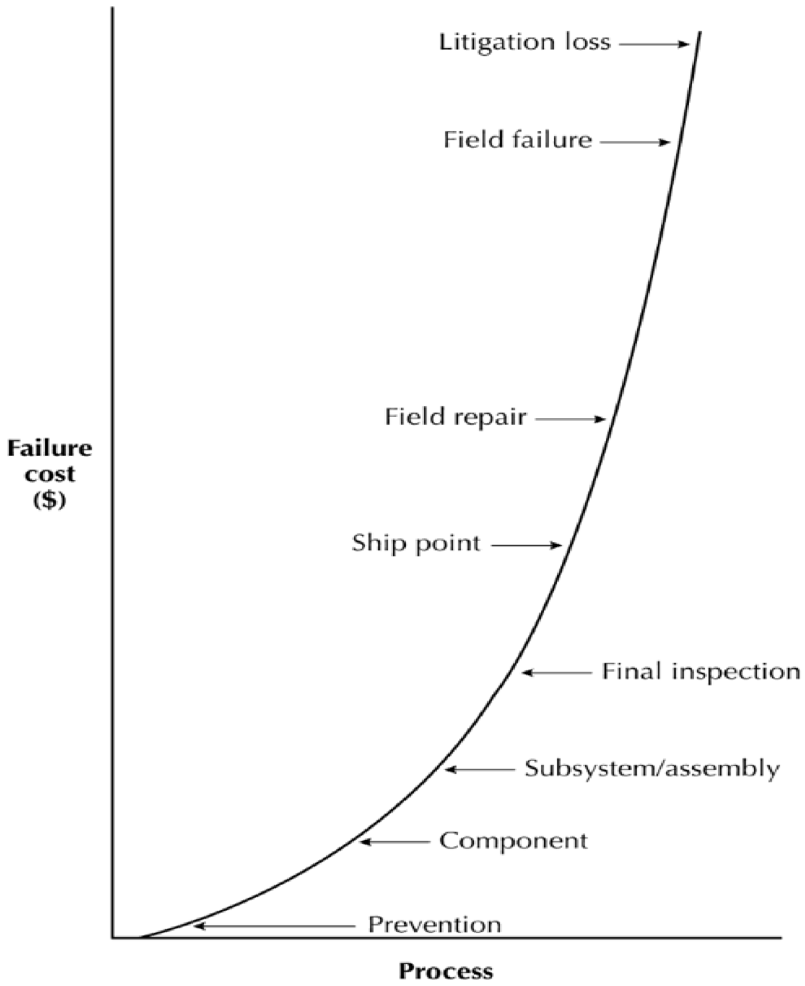


Figure 5. Failure cost as a function of detection point in a process (Wood, 2012)

4.4 Manual Visual Inspection vs. Machine Vision

According to the Federal Aviation Administration (FAA), visual inspection is defined as “the process of using the unaided eye, alone or in conjunction with various aids, as the sensing mechanism from which judgments may be made about the condition of a unit to be inspected” (Harish, 2015) . Despite its widespread application in quality control, particularly in the automotive and aerospace sectors, the accuracy of 100% manual visual inspection is inherently limited. As noted in Juran’s Quality Handbook, even under ideal conditions, human inspectors can achieve no more than 87% accuracy in defect detection. To approach near-perfect accuracy (99,7%), manual inspection would need to be repeated approximately three times, a concept referred to as “300% inspection” (De Feo, 2017) .

In automotive manufacturing, quality control traditionally relies on manual visual inspection, where trained inspectors assess components for surface anomalies, alignment issues, and missing elements. While this method is well-established and offers flexibility in interpreting ambiguous scenarios, it is increasingly challenged by rising production speeds, stricter quality standards, and workforce limitations. Machine vision systems, enhanced by artificial intelligence, have emerged as a robust alternative, offering automated, consistent, and real-time defect detection capabilities. The following comparison outlines the key differences between manual visual inspection and AI-powered machine vision, focusing on operational performance, consistency, adaptability, and integration within industrial environments.

According to Anand and Priya (2019), the six points below summarize the key distinctions between machine vision systems and manual inspection in industrial quality control, highlighting their respective advantages and limitations:

- Speed and Efficiency: Machine vision systems operate at high speeds, capable of inspecting hundreds of items per minute without fatigue or interruption. Their automated processing allows for continuous real-time inspection, significantly improving production throughput. Manual inspection is limited by human attention span and physical constraints. Inspectors require regular breaks, and inspection time increases with task complexity, making it less efficient for high-volume production.

- Cost Implications and Investment: Although the initial investment in machine vision systems can be high due to equipment, installation, and integration, the long-term operational costs are low. The system reduces labor costs and minimizes rework through early defect detection. Manual inspection incurs lower initial costs but higher recurring costs due to labor wages, training, and error-related rework. Over time, this results in higher total cost of ownership, especially in large-scale manufacturing.

- Consistency and Accuracy: Machine vision provides highly consistent results as it eliminates subjectivity. The system maintains the same inspection criteria across all products and shifts, ensuring stable quality control outcomes. Manual methods are subject to variability due to fatigue, distractions, and differences in inspector judgment. This inconsistency may lead to undetected defects or false rejections.

- Adaptability and Decision-Making: With AI integration, machine vision systems can learn from data and adapt inspection parameters over time. However, decision-making is limited to predefined algorithms and training data. Manual Inspection, Human inspectors can apply flexible decision-making in complex or unforeseen situations. They can use intuition and experience, which machine systems currently cannot replicate fully.

- Operational Environment and Conditions: Machine vision performs reliably in challenging conditions, including poor lighting, hazardous environments, or repetitive tasks, as long as proper system calibration and shielding are maintained. Manual Inspection, Humans are sensitive to environmental factors such as lighting, temperature, and ergonomic strain. These conditions can reduce accuracy and increase error rates over time.

- Scalability and Integration: Machine vision is highly scalable and integrates seamlessly into automated production lines. New cameras or inspection tasks can be added with minimal disruption to operations. Manual Inspection, scaling manual inspection requires proportional increases in human resources, space, and training. This makes it less flexible and more difficult to expand efficiently.

Summary

The comparison highlights that while manual inspection remains valuable for handling variability and complex decision-making, machine vision systems outperform in speed, consistency, scalability, and data integration. Automated inspection reduces reliance on human judgment, minimizes labor costs, and ensures higher accuracy in detecting repetitive and visually discernible defects. As Valmet Automotive explores AI-enhanced quality control, these insights underscore the strategic benefits of transitioning from manual to automated systems, particularly in high-volume, precision-sensitive assembly lines.

4.5 Machine Vision Technologies in Automotive Industries

Machine vision technology refers to the use of optical sensors (cameras) and computational algorithms to enable machines to "see" and interpret visual information for industrial tasks (Premio Inc. 2021). In the automotive manufacturing sector, machine vision is a foundation of modern quality control and assembly verification. It allows for automated inspection of parts and vehicles at high speed and with high consistency, improving upon manual inspection in both reliability and output (Mdpi, 2024).

Key advancements in this area combine artificial intelligence (AI), computer vision, and robust industrial hardware to detect defects or assembly errors in real time. Two prominent approaches in automotive machine vision are AI-powered smart cameras and vision tunnel systems, each with diverse functionalities and advantages. Advanced cameras and algorithms today inspect critical parts and assemblies to detect defects far beyond human capabilities.

This sub-chapter reviews the state of the art in machine vision for quality control of automotive components, covering its applications, real-world case studies, and a comparative analysis of key technologies. I will define machine vision and artificial intelligence (AI), and explore how AI techniques are integrated into machine vision systems to enhance their capabilities, I will also examine various camera types (2D, 3D, infrared, ultraviolet, hyperspectral), sensor technologies (CMOS, CCD, time-of-flight), and software algorithms (rule-based image processing vs. AI/ML). Different system configurations from single AI-powered smart cameras to multi-camera vision tunnel systems are compared in terms of capabilities, cost, and performance trade-offs. Throughout, I will cite industry studies, implementations, and vendor data relevant to automotive quality control to ground the discussion in real-world evidence.

4.5.1 Machine Vision

Machine vision represents a specialized area within the broader field of computer vision, specifically addressing industrial applications through the utilization of cameras, sensors, and sophisticated algorithms to analyze visual data and support automated decision-making processes in real-time (Pandharipande et al., 2023). Within the automotive industry, this technology is widely applied to critical tasks, including quality assurance, defect detection, and automation of assembly line processes, thereby enhancing efficiency, accuracy, and consistency of production (Hoang, 2024).

In automotive assembly lines, machine vision systems might verify the presence and proper placement of screws in engine components, measure door-to-body gaps, or guide robotic arms during sealant application (de Souza Silva & Paladini, 2025). A deciding factor between machine vision and pure computer vision lies in machine vision's emphasis on real-time data processing and robust integration into industrial workflows. Machine vision systems must often inspect components within fractions of a second, conforming to production line cycle times, necessitating high-speed cameras and advanced processing units such as Graphics Processing Units (GPUs) and Field-Programmable Gate Arrays (FPGAs) accelerators (Frustaci et al., 2022).

Modern machine vision systems increasingly leverage AI, specifically deep learning techniques, to handle complex inspection tasks more effectively. AI-driven machine vision systems are not only capable of detecting predefined defects but also excel in identifying complex and variable anomalies previously challenging for manual or traditional automated systems (Tzampazaki et al., 2024; Islam et al., 2024). Therefore, automotive manufacturers widely adopt machine vision for non-contact dimensional measurements, surface defect detection, assembly verification, and automated code reading, significantly improving production consistency and defect detection efficiency (Javaid et al., 2022; de Souza Silva & Paladini, 2025).

4.5.2 Artificial Intelligence in Machine Vision

Machine vision (MV) has become an essential component in modern manufacturing environments, particularly as a method for automated quality inspection.

According to Pérez et al. (2016), these systems are commonly integrated into the production line, ensuring that each product undergoes inspection before progressing to the next stage. A typical MV configuration includes one or more cameras, a processing unit (commonly a PC), and a lighting system housed within a controlled enclosure to ensure stable and repeatable inspection conditions.

Machine learning (ML) and deep learning (DL) are data-driven artificial intelligence (AI) methodologies that can be effectively applied within machine vision (MV) systems. Both techniques are based on neural network architectures that transform raw image data into structured representations to support decision-making processes in industrial environments. In traditional ML applications, the process is typically divided into separate stages: manual feature extraction and classification. These stages are implemented independently, often relying heavily on domain-specific expert knowledge. On the contrary, DL integrates feature extraction and classification into a unified neural network structure, significantly reducing the need for manual intervention. This end-to-end architecture enables the system to learn directly from data, thus enhancing adaptability and performance.

As illustrated in Figure 6, the structural and procedural differences between traditional machine learning and deep learning approaches in the context of machine vision systems. The upper path, labeled 1*, represents traditional machine learning, where the process begins with manual feature extraction and selection. In this method, domain experts are required to define and extract relevant features from preprocessed image data. These features are then passed into a separate classification learning model, which interprets the data to make predictions or decisions. This workflow is inherently dependent on expert knowledge and structured input data.

In contrast, the lower path, labeled 2*, depicts the deep learning approach, where both feature extraction and classification are integrated into a single, unified neural network structure. Deep learning models, particularly convolutional neural networks (CNNs), automatically learn relevant features from raw input data, reducing the need for manual intervention. This end-to-end learning capability enables higher flexibility and accuracy in complex visual tasks, especially in environments where large volumes of image data are available. The figure 6. effectively highlights how deep learning eliminates the need for handcrafted feature engineering, thereby increasing efficiency, reducing human error, and enhancing adaptability in visual inspection processes (Wang et al., 2018).

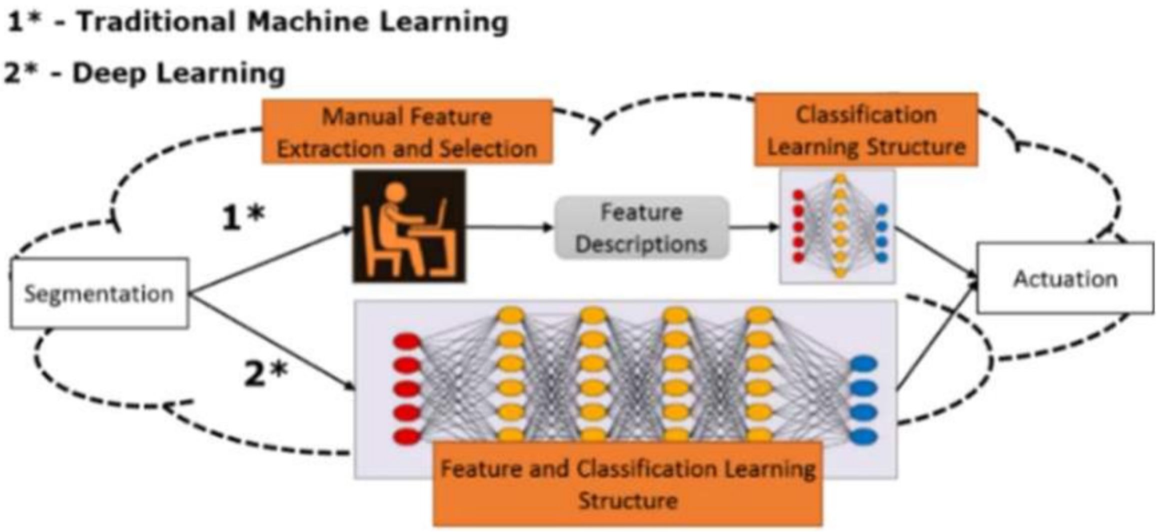


Figure 6. Comparison between machine learning and deep learning in machine vision, (Wang et al. 2018).

One of the main limitations of machine vision (MV) systems that do not incorporate artificial intelligence (AI) techniques is their inability to learn from previously processed images. Typical MV systems operate based on predefined parameters set during initial configuration, which means any newly emerging defects or minor variations introduced in the production process may go undetected.

Golnabi and Asadpour (2007) introduced a foundational block diagram illustrating the operational flow of a conventional MV system during the early development of AI integration. Based on that structure, a revised version was developed to incorporate modern AI functionalities identified in recent literature. This enhanced framework is illustrated in Figure 7. presents a comprehensive block diagram depicting the architecture of a typical machine vision system (MVS) used in industrial quality control, extended with artificial intelligence techniques. The system begins with the acquisition of optical data, where external or emitted light is captured through image sensors and converted into digital signals. These signals are then processed through a series of stages, including preprocessing and segmentation, to isolate the relevant image regions. In traditional implementations, the system depends on a predefined knowledge base, containing object features and quality criteria, to perform comparisons and generate inspection outputs.

The figure 7. further incorporates advanced AI modules into the vision pipeline. These include feature extraction, classification, and interpretation components, which are powered by machine learning and deep learning models. These AI techniques enhance the system's adaptability by enabling it to learn directly from image data rather than relying solely on rule-based criteria. A central data storage component, which may utilize remote or cloud infrastructure, supports the learning cycle by archiving feature information and inspection outcomes. The integration of a human-machine interface (HMI), network communication, and image display elements allows for real-time feedback, visualization, and interaction with the inspection system.

This AI-enhanced architecture enables the machine vision system to go beyond static inspection capabilities by learning from previously unseen image inputs, thereby improving fault detection accuracy and supporting dynamic adaptation to new product variants or quality deviations. Figure 7. Block diagram of a machine vision system with integrated artificial intelligence techniques, adapted from Silva et al. (2018), effectively illustrates the synergy between traditional vision processing and AI-driven enhancements, aligning with current trends in intelligent manufacturing and Industry 4.0 environments.

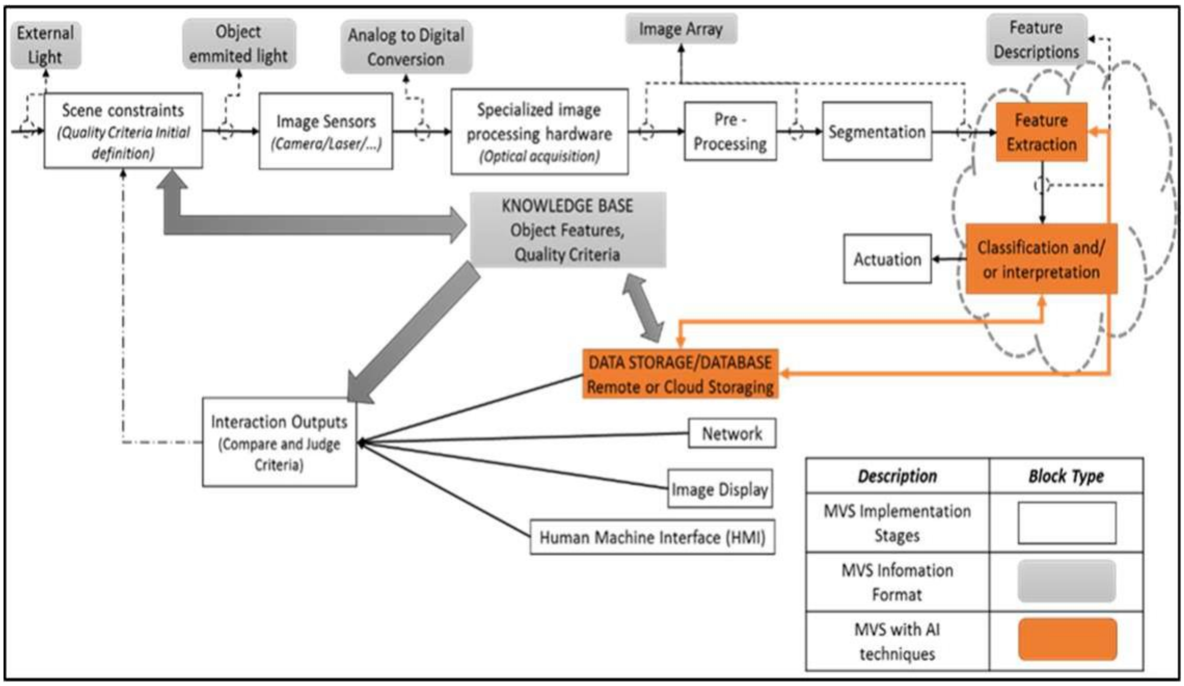


Figure 7. Block diagram of a machine vision system with integrated artificial intelligence techniques (Silva, Rudek, Szejka, & Junior, 2018)

4.5.3 Machine Vision Technologies

Components. Machine vision systems integrate image acquisition and digital processing to enable automated quality inspection in industrial environments. These systems rely on high-quality image capture and robust component integration to ensure accurate data extraction and decision-making. Their effectiveness is rooted in selecting suitable optical, mechanical, and software components that allow 24/7 operation under high-speed and repetitive conditions. This section introduces the core hardware and software elements typically found in machine vision systems and emphasizes their role in ensuring reliable performance in manufacturing applications (Anand, S. & Priya, L. 2019).

4.5.3.1 Components of Machine vision

A machine vision system comprises several critical components that work in coordination to enable automated inspection. These include lighting, lenses, image sensors, vision processing units, and communication interfaces. Lighting is essential to illuminate the object under inspection, enhancing surface features so that they can be accurately captured. The lens focuses this light onto the image sensor, which converts it into a digital signal representing the visual characteristics of the object. This digital image is then processed using vision algorithms that extract relevant features, perform necessary measurements or classifications, and generate inspection decisions Cognex (2024).

The configuration and selection of these elements are directly influenced by the intended application and the required level of automation. For instance, in quality control applications where objects remain stationary, it is often sufficient to employ a single camera system capable of capturing high-resolution static images for inspection purposes (Anand, S. & Priya, L. 2019)

A representative example of a machine vision system is illustrated in Figure 8. In this configuration, a single camera captures the image of the target object for analysis. Depending on the application requirements, the system may incorporate one, two, or several cameras to ensure comprehensive and reliable image acquisition.

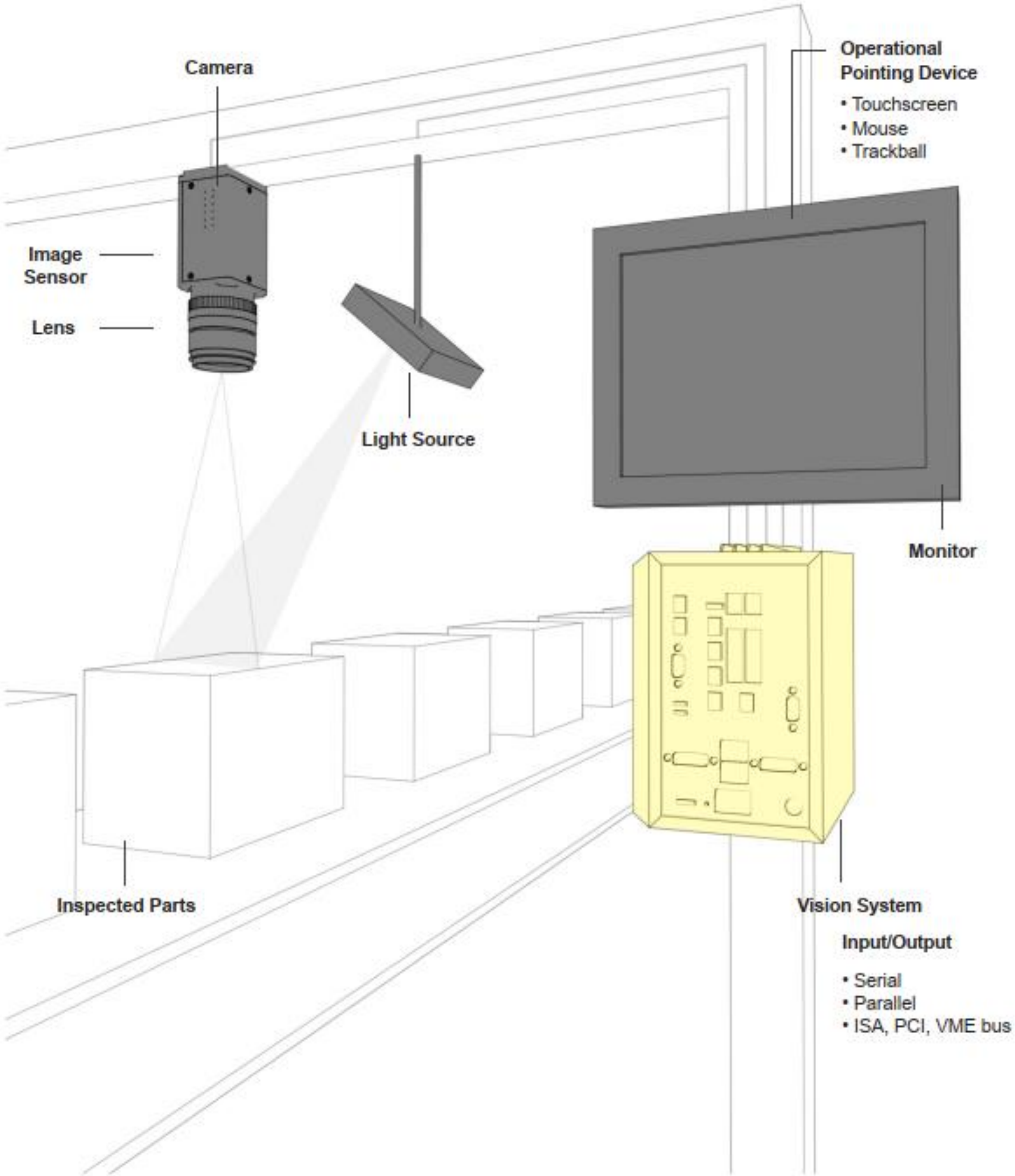


Figure 8. Main components of a machine vision system Cognex (2024).

Lighting in Machine Vision Systems:

According to Cognex (2024) Effective lighting is a fundamental prerequisite for achieving accurate and reliable machine vision outcomes. Rather than observing the object itself, machine vision systems interpret the reflected light captured by the camera. Therefore, the position, type, and direction of the light source in relation to the inspected object and the camera directly influence image quality and the visibility of specific features. Proper lighting setup can enhance desired characteristics or suppress irrelevant details to optimize defect detection and dimensional assessment.

According to Anand and Priya (2019), lighting plays a critical role in machine vision systems as it directly affects image quality and the ability to detect key object features such as edges, colors, and textures. Properly controlled lighting enhances the visibility of these features, thereby improving inspection accuracy. Common light sources include LED arrays, which provide efficient and uniform illumination, fluorescent lamps, used for soft and diffused lighting in large-area inspections; and halogen lights, which deliver high-intensity light for detailed tasks. Additionally, lasers are employed for precise measurements through structured lighting patterns. The choice of lighting depends on the inspection context and desired visual contrast in the captured images.

Lighting Techniques in Machine Vision

In machine vision systems, lighting is not merely a supplementary component but a foundational element that directly impacts image quality, feature visibility, and inspection accuracy. Selecting appropriate lighting techniques is essential for capturing consistent, high-contrast images that facilitate reliable defect detection and component verification. Different inspection scenarios require tailored lighting strategies to address variations in surface characteristics, object geometries, and environmental conditions (Anand, S. & Priya, L. 2019).

Key techniques include seven distinct lighting methods, each applied based on the specific requirements of the inspection task (Cognex 2024).

Back Lighting: Commonly used for silhouette imaging, this technique emphasizes the object's outer contours. It is especially effective for edge detection and dimensional measurements.

Axial Diffuse Lighting: Light is introduced coaxially using a semi-transparent mirror to achieve uniform illumination. This method is useful for highlighting flat surfaces and minimizing shadows.

Structured Light: A light pattern plane, grid, or complex shape is projected at a known angle onto an object. This allows surface profile measurements and volume estimation, offering robustness against variations in surface contrast.

Dark-field Illumination: Particularly effective for detecting low-contrast surface anomalies, this technique reflects diffused light from minor surface texture deviations back to the camera while redirecting direct reflections away.

Bright-field Illumination: Suitable for high-contrast inspections, this technique illuminates the object directly. However, issues like specular reflections and uneven lighting may occur, especially with reflective surfaces.

Diffused Dome Lighting: This configuration ensures even lighting across the entire field of view and is ideal for minimizing glare and highlighting features uniformly.

Strobe Lighting: Used in high-speed inspection scenarios, strobe lighting freezes motion to prevent blur, enabling precise imaging of moving parts.

Based on the description above, effective lighting is essential for ensuring high-quality results in machine vision systems, as the systems rely on analyzing reflected light rather than directly observing the object. Lighting type, direction, and placement strongly influence the visibility of relevant features and the suppression of irrelevant details.

For the AI camera inspection before windshield gluing, dark-field and diffused dome lighting are recommended. These lighting methods reduce glare and allow for the detection of anomalies such as extra components, misrouted wires, or foreign parts in the inspection area near the windshield frame.

For door surface inspection in a vision tunnel, a combination of dark-field illumination, structured light, and diffused dome lighting is ideal. Dark-field lighting enhances the visibility of fine surface defects like scratches and dents, structured light supports dimensional analysis and contour verification, and dome lighting ensures uniform illumination to reduce specular reflections.

Proper lighting selection, therefore, plays a critical role in optimizing the machine vision system’s performance, particularly in detecting low-contrast defects, maintaining image consistency, and ensuring accurate inspection across various materials and surface types.

Lenses:

When selecting a lens for a machine vision application, several parameters must be carefully evaluated to ensure optimal performance. These include the resolution of the camera sensor, the working distance between the camera and the inspected object, the physical dimensions of the object, and the amount of ambient or directed lighting available in the inspection environment. The resolution of the camera sensor directly influences lens selection. In cases where a high-resolution sensor is available, the need for strong optical magnification is reduced, as digital zoom capabilities can be used to enlarge image details post-capture. This makes it possible to use lenses with a broader field of view, allowing more content to be captured within a single frame. Conversely, if the system employs a lower-resolution camera, achieving the necessary visual clarity for quality inspection may require a lens with a longer focal length. This ensures sufficient optical magnification to resolve critical surface or structural features relevant to the application (Anand, S. & Priya, L. 2019)

According to Cognex (2024) Lenses play a crucial role in image quality by focusing light onto the camera sensor. They vary in optical quality and cost and are available in fixed and interchangeable types. Interchangeable lenses such as C-mount or CS-mount enable greater flexibility, while fixed lenses often include autofocus features. The correct lens and extension configuration directly influence the resolution and clarity of the captured image.

Image Sensors: The image sensor converts light into electronic signals and is central to the system's ability to generate usable images. Common sensor types include Charge-Coupled Device (CCD) and Complementary Metal-Oxide-Semiconductor (CMOS). These sensors transform light into a pixelated digital image where brighter light yields higher pixel intensity. Selection of the sensor resolution is essential, depending on the size of the component and required inspection tolerances.

Vision Processing: Vision processing involves extracting meaningful information from digital images. Processing can occur internally (in a standalone vision unit) or externally via a PC-based system. The process includes image acquisition, pre-processing, feature recognition, measurement, specification comparison, and final decision-making. While many vision systems share similar hardware, the underlying software algorithms play a pivotal role in performance differentiation. They determine camera settings, perform inspections, log data, and interface with factory systems.

Communications:

Machine vision systems require seamless integration with other automation elements. Communication can occur through discrete I/O signals or digital protocols such as RS-232 or Ethernet. Advanced setups may utilize industrial protocols like Ethernet/IP to transmit data to Programmable Logic Controllers (PLCs), monitors, or operator interfaces. These systems facilitate process monitoring, inspection result communication, and automated decision-making, such as activating reject mechanisms Cognex (2024).

In summary, successful implementation of machine vision hinges on optimal lighting, accurate lenses, suitable sensors, robust processing algorithms, and seamless communication within the production environment.

4.5.3.2 Camera Types and Imaging Modalities

In the context of automotive manufacturing, particularly in quality control of vehicle exteriors and structural components, selecting the appropriate machine vision modality is critical. This subchapter discusses the main types of camera systems used in industrial environments specifically 2D line-scan cameras and 3D vision systems due to their practical relevance for inspecting vehicle doors and for monitoring the station prior to windshield installation at Valmet Automotive.

Machine vision (MV) systems can generally be classified into three main categories based on dimensional data acquisition: one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) systems, in this section I will focus more on 2D and 3D, due to their relevancy of my thesis topic. Machine vision contains a broad range of hardware and software technologies. Here we compare the major categories relevant to automotive metal part inspection:

2 D Line-Scan Cameras

Line-scan cameras are essential imaging tools in industrial environments, particularly where products are transported via conveyor systems. In such setups, stopping the conveyor to capture images for inspection would be impractical and disruptive. Therefore, conveyors typically operate at a steady, controlled speed, enabling continuous imaging. Line-scan cameras are well suited to these applications as they capture images line-by-line using a single row of photodetectors integrated on a sensor chip. These cameras are designed to acquire images in synchronization with the movement of the object, making them highly efficient for high-speed inspection of products in motion. Appropriate lighting such as long tube lights aligned parallel to the scan line and perpendicular to conveyor movement is critical to ensure image clarity and uniformity (Davies, 2012).

A special subset of 2D imaging, line-scan cameras capture one line of pixels at a time at high speed. As either the part or camera moves, these lines compose a very high-resolution continuous image. Line-scan vision is used for inspecting large metal sheets or coils for surface defects, or rotating a part in front of a camera to inspect its entire circumference. For example, inspecting a long strip of steel for scratches or a cylindrical part (by spinning it) often employs line-scan imaging to achieve consistent high resolution. While powerful, line-scan systems require precise synchronization with motion and are typically used in niche automotive applications (like steel mill inspection for automotive-grade steel) .This method is particularly advantageous for inspecting continuous or moving materials and is depicted in Figure 10. Cognex (2024).

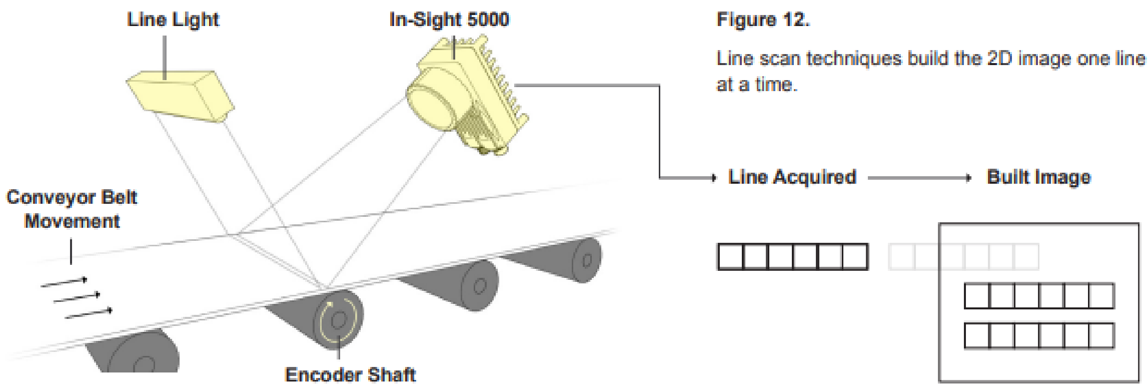


Figure 9. Line scan techniques build the 2D image one line at a time Cognex (2024).

3D Cameras and Sensors

According to Cognex (2024) 3D machine vision systems are generally composed of multiple cameras or incorporate one or more laser displacement sensors, depending on the application requirements. In robotic guidance applications, multi-camera setups are commonly used to determine the spatial orientation of parts. These systems operate based on the principle of triangulation, where cameras are strategically positioned at different angles to calculate the precise location of objects in three-dimensional space.

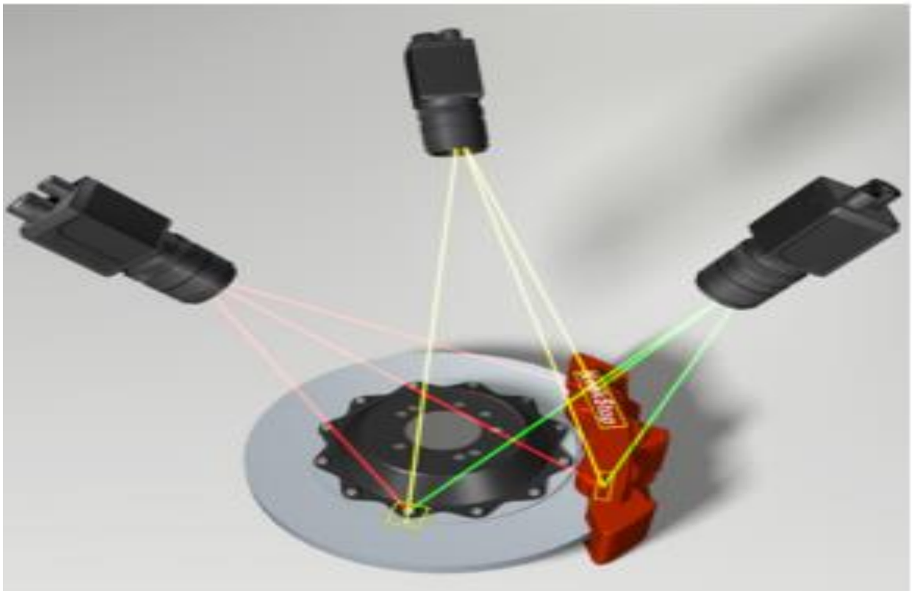


Figure 10. 3D Vision typically employ multiple cameras (Cognex, 2024).

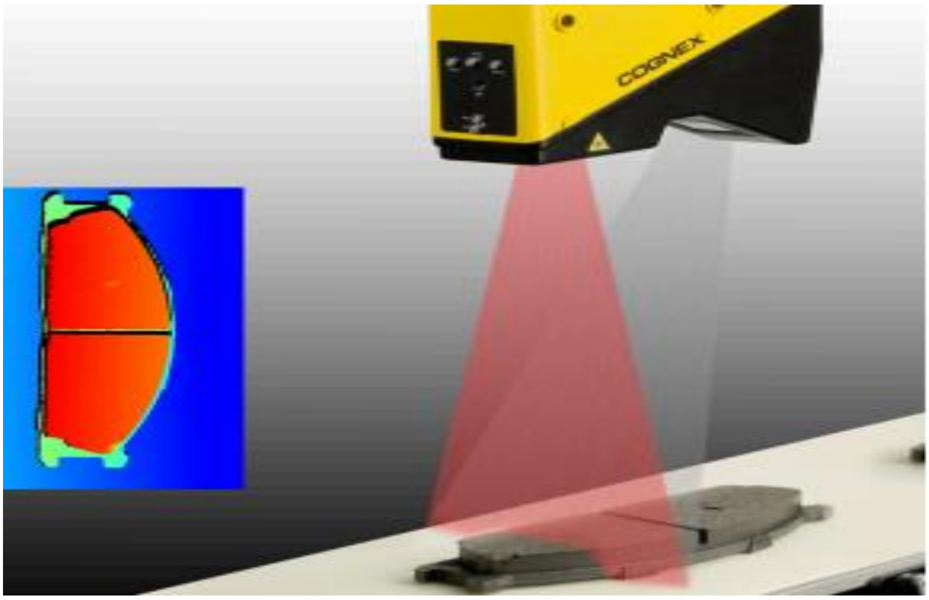


Figure 11. 3D Inspection using a single camera (Cognex, 2024).

In contrast, 3D laser displacement sensor systems are widely applied in tasks such as surface inspection and volumetric measurement. These systems can generate accurate 3D representations using as few as a single sensor. A height map is produced by measuring the displacement of reflected laser points on the object's surface. Similar to line scan techniques, either the object or the sensor must be in motion to capture the full surface profile. When integrated with a calibrated offset laser, displacement sensors are capable of performing precise measurements such as surface height and planarity, achieving accuracies within 20 micrometres. An example of such an application is presented in Figure 12, where a 3D laser displacement sensor is used to inspect the surface of a brake pad for defects (Cognex, 2024).

Table 2 compares these camera modalities, summarizing their typical uses, advantages and limitations in automotive metal part inspection:

Table 2. Comparison of Camera Types for Automotive QC

Camera Type	**Typical Uses in Automotive QC**	**Advantages**	**Limitations**
2D Area-Scan	Surface defect detection (scratches, dents), presence/absence checks, label/code reading on parts.	Fast, affordable, mature technology. High resolution available for fine detail.	No depth information, sensitive to lighting and glare, requires good contrast between defect and background.
Line-Scan 2D	Continuous surfaces: inspecting metal coils or large panels, or rotating parts for 360° surface check.	Very high resolution for large or moving objects, uniform inspection of long parts.	Needs precise motion control, cannot capture an area instantaneously (only line by line).
3D Structured Light / Laser	Dimensional inspection (gap & flush, hole positions), weld bead profiling, detecting dents or deformations in metal parts.	Provides accurate depth and shape measurement, not as affected by color or ambient lighting.	Higher cost and complexity, typically slower throughput, requires calibration.

As seen, each modality has a role: 2D vision is ubiquitous for general inspection, 3D addresses spatial verification needs that 2D cannot tackle particular problems or enhance contrast when normal imaging falls short. Most automotive quality systems combine multiple techniques, for instance, a paint inspection tunnel might use standard RGB cameras with polarized lighting for gloss evaluation, plus a fringe projection setup for detecting small dents (3D). The choice depends on the defect types to be caught and the required accuracy. For precise detection of part misalignment and gap and flush variations in automotive manufacturing, 3D machine vision systems are the most effective choice. These systems provide accurate, non-contact measurements of spatial relationships between components, ensuring consistent alignment and high-quality assembly.

Summary

In summary, this subchapter demonstrates that the selection of an appropriate imaging modality 2D or 3D depends on the nature of the defects, the inspection location, and the required level of precision. For Valmet Automotive, 2D line-scan cameras are particularly well suited for inspecting the area before windshield gluing, where the production line is in continuous motion and the goal is to detect surface anomalies or verify the presence of components. In contrast, 3D machine vision systems are more appropriate for door inspections, where accurate detection of gap and flush deviations is essential to ensure structural integrity and visual alignment during final assembly.

4.5.3.3 Sensor Types CMOS and CCD

The core of any camera is its image sensor. Two main sensor technologies have been used in machine vision cameras:

- CCD sensors transport charge across the chip and convert it to voltage at a common output node, a process that delivers high image quality with minimal noise. This uniform readout method ensures excellent image consistency and sensitivity, making CCDs especially suitable for scientific imaging and industrial applications requiring high precision. However, CCDs are generally more power-hungry, slower in readout, and more expensive to manufacture compared to CMOS sensors (Diffraction Limited, 2021, p. 5–6).

- CMOS sensors, by contrast, contain amplifiers and analog-to-digital converters at each pixel, enabling faster readout speeds and significantly reduced power consumption. Modern CMOS technology has overcome historical disadvantages such as fixed pattern noise and lower sensitivity, offering high resolution, real-time imaging, and on-chip processing capabilities. These features make CMOS ideal for high-speed manufacturing applications and embedded machine vision systems (Diffraction Limited, 2021, p. 7–9).

Table 3 provides a brief comparison of CCD vs CMOS for context:

Table 3. CCD vs CMOS Sensor Characteristics (Diffraction Limited, 2021)

Sensor	Characteristics	Usage in Automotive Vision
CCD	High image quality, low noise, often global shutter by design. Slower frame rates, higher cost per sensor.	Early generation systems and some high-precision measurement cameras. Largely phased out as of 2025 in favor of CMOS except special cases.
CMOS	Very fast frame rates, high resolution, lower cost. Modern global shutter CMOS have excellent image quality, rolling shutter types also exist (used in some lower-cost smart cameras).	Nearly all new vision systems: e.g., smart cameras by Cognex, Keyence use CMOS, multi-camera inspection stations use CMOS GigE/USB cameras. Enable high-speed inspections and multi-camera setups within budget .

Summary

In the evolution of machine vision systems, both CCD (Charge-Coupled Device) and CMOS (Complementary Metal-Oxide-Semiconductor) sensors have played significant roles. However, in modern automotive manufacturing environments such as Valmet Automotive, CMOS sensors have become the dominant choice due to their clear advantages in speed, power efficiency, and cost-effectiveness. These attributes make CMOS sensors particularly well-suited for both line-scan and area-scan camera systems used in high-throughput inspection stations for example, at the pre-windshield gluing stage or during detailed door surface inspections.

CMOS technology supports high-resolution imaging and fast frame rates necessary for real-time defect detection, while also offering seamless integration with existing production line systems. Recent advancements have led to the use of sensors exceeding 20 megapixels, allowing larger vehicle components such as hood panels to be captured by a single camera, thereby reducing the total number of cameras required. However, higher resolution also demands increased data processing capacity, which must be carefully balanced against available computing resources to maintain real-time operational performance.

While CCD sensors may still be present in legacy systems or specialized high-fidelity applications particularly in scientific or laboratory-grade inspections their use in automotive manufacturing is increasingly rare. The industry's emphasis on robustness, speed, and scalability strongly favors CMOS technology, which offers the optimal trade-off between image quality and practical implementation constraints.

In conclusion, for Valmet Automotive’s specific use cases, CMOS sensors provide the most suitable technological foundation for building efficient, scalable, and high-performance machine vision systems that align with the company’s quality assurance objectives and production requirements.

4.5.3.4 Algorithms and Software in AI-Driven Machine Vision for Defect Detection

This sub-section introduces the core AI-based techniques used for defect detection, particularly supervised and unsupervised learning approaches. These methods enable systems to recognize complex visual patterns, detect surface anomalies, and adapt to new defect types. Understanding the capabilities and limitations of each algorithm type is essential for selecting an appropriate solution for different inspection tasks at Valmet Automotive.

The “brain” of a machine vision quality system is the software that analyzes images to identify defects or measure features. There is a spectrum from traditional, rule-based image processing to modern AI (artificial intelligence) and machine learning approaches. Often, a combination is used to achieve the best results. Within this section, I will focus on AI-Driven Machine Vision.

Supervised Defect Classification Artificial Intelligence & Machine Learning: AI/ML approaches, especially deep learning with convolutional neural networks (CNNs), have revolutionized machine vision in the last 5-6 years. Instead of manually programming what a defect looks like, the system is “trained” on many images. Two broad approaches are used:

Supervised learning approaches in machine vision involve training AI models with labeled datasets containing examples of both acceptable ("good") and defective ("bad") parts. Tools like Cognex's VisionPro Deep Learning suite facilitate this by allowing users to train convolutional neural networks (CNNs) to detect specific defects such as scratches or dents on metal surfaces. The software's Red Analyze tool, for instance, is designed for defect detection and segmentation, enabling the identification of subtle anomalies on various backgrounds and textures. However, the effectiveness of supervised learning heavily relies on the availability of a substantial dataset of labeled images, which can be challenging to compile, especially when defects are rare or diverse (Cognex Corporation, 2024).

Anomaly Detection (Unsupervised) A very popular method in high-mix, low-defect scenarios (like final car inspection) is to train the AI only on good part images. The model (e.g., an autoencoder or a one-class classifier) learns the normal appearance of the part. During inspection, any deviation from this learned “normal” pattern is flagged as an anomaly (potential defect). This is how the Inspekto S70 system works: it uses pre-trained general models and adapts to the new part by feeding it a few dozen known-good images. It then signals if a new image looks different from the good ones, leaving the human to verify if it’s an actual scratch, missing piece, etc. This approach was effective for BMW’s needs because they only needed to show good engine assemblies to train the system, and it could then catch an improperly locked sensor clip as an anomaly (Vision Systems Design, 2020)

Summary

AI-based vision systems have demonstrated considerable effectiveness in surface defect detection, particularly on metal components where conventional methods often struggle due to reflections, noise, or subtle visual variations. For example, identifying fine scratches or minor deformations on reflective surfaces poses a significant challenge for traditional image processing techniques. AI and machine learning (ML) approaches, particularly those based on deep learning, can address these limitations through advanced feature extraction and pattern recognition. However, such systems demand large volumes of labeled data, substantial computational resources, and specialized hardware such as GPUs to support both training and inference. Furthermore, while inference times for AI models are typically slower than simpler techniques like blob detection, the continuous advancement of optimized libraries and hardware accelerators is improving the feasibility of real-time AI applications in industrial settings.

For Valmet Automotive, the most suitable solution depends on the inspection context. At the pre-windshield gluing station, where consistent components such as clips, wires, and trim elements are checked, a hybrid approach combining supervised and unsupervised learning is recommended. Supervised models can accurately detect known defect types (e.g., missing clips), while anomaly detection algorithms add flexibility by flagging unexpected issues or misassemblies not seen in training data.

In contrast, for door inspections where surface anomalies like scratches or misalignments are prevalent a supervised learning model trained on labeled defect images would be more effective, assuming sufficient data availability. This method ensures high detection accuracy for common defect patterns on painted or reflective surfaces. Overall, combining AI software strategies based on inspection requirements enables an effective and scalable quality control solution at Valmet Automotive.

4.5.3.5 System Configurations and Mounting Setups

In automotive manufacturing, the configuration of vision systems plays a central role in ensuring product quality and production efficiency. I will focus on two prevalent setups are fixed overhead or side-mounted cameras and conveyor tunnel systems equipped with multi-camera arrays. This sub-section presents two widely used configurations fixed camera installations and conveyor-based tunnel systems. Both approaches offer different strengths and limitations depending on inspection targets, available space, investment level, and the desired degree of automation. These insights are particularly relevant for Valmet Automotive, where vision-based inspection is gradually integrated into selected stages of final assembly.

Fixed Overhead or Side Cameras A simple setup is a camera (with lighting) mounted at a fixed position over a conveyor or station where parts pass. For example, a downward-looking camera might inspect each machined part on a conveyor for missing holes. This is relatively low-cost and easy to implement but limited to the views that camera sees. To get multiple angles, multiple fixed cameras can be arranged (e.g., two cameras at 45° angles to inspect the sides of a part, while one looks top-down). Fixed mounts are very common in component inspection (like checking an engine block on a pallet from above). They offer high speed since no time is lost in moving equipment – the part can even be in motion as images are taken (with appropriate trigger timing). The challenge is they are inflexible once installed, any change in part or feature to inspect might require repositioning or adding cameras (Trivedi, 2024).

Conveyor Tunnel (Multi-Camera Array) As described with vision tunnels like the Eines system, multiple cameras are arranged around a part’s path to capture all necessary views in one go. In a conveyor tunnel for car bodies, there might be, for example, 20+ cameras: covering front, rear, sides, top, and various angles, along with specialized lighting (bright field, dark field, structured patterns). The part (a full car or a large component) passes through without stopping, and all cameras trigger in sync to image different areas. The result is a comprehensive set of images for that unit, which are then processed in parallel. This configuration is ideal for 100% inspection at full line speed, since it doesn’t require stopping or manual intervention. It is, however, the most complex and costly setup (see Section 3.5 on cost trade-offs). Such systems need careful optical engineering to avoid cameras interfering (cross-talk of lighting) and enormous processing capabilities to handle many high-res images in real time. Calibration to stitch measurements (like aligning gap measurements from different cameras around a door) is also non-trivial. Despite this, many OEMs have either installed or are evaluating these systems for final inspection, as they promise uniform quality control for every vehicle (Konica Minolta Sensing, 2025). See figure 14. below

Figure 12. Tunnel Vision Systems Solutions for the Automotive Industry (Konica Minolta Sensing, 2025).

Summary

In conclusion, fixed camera systems, typically positioned above or beside production lines, present a cost-effective and relatively simple solution for inspecting specific components or features, such as verifying the presence of holes in machined parts or performing targeted checks like windshield pre-gluing verification. Their implementation allows for minimal disruption to production flow. However, their limited field of view often necessitates the use of multiple cameras to cover various angles, and any changes in inspection requirements may require manual adjustment or reconfiguration of the hardware.

Conversely, conveyor tunnel systems such as those developed by Eines integrate multiple high-resolution cameras and specialized lighting setups to provide comprehensive, real-time inspection of entire vehicles as they move through the production line. These systems enable extensive surface quality assessments, dimensional checks, and component presence verification without halting production. Despite their advantages in automation and coverage, they require significantly higher technical complexity and financial investment.

For manufacturers such as Valmet Automotive, understanding the respective advantages and limitations of these configurations is critical for developing an efficient and scalable quality control strategy. A phased approach beginning with fixed camera systems for high-priority inspection points and progressively advancing toward tunnel-based systems offers a pragmatic pathway to enhance inspection capabilities while managing operational and financial constraints.

4.5.3.6 Applications of Machine Vision and Typ of Production in Quality Control

According to Hornberg (2017), these applications can be categorized into six principal functional groups. Code recognition involves the identification of components using coded markings such as barcodes or DataMatrix symbols, often used in logistics and materials tracking. Object recognition refers to the detection and differentiation of parts based on distinct visual features such as shape, dimensions, color, or surface texture, with growing relevance of 3D data to improve accuracy and robustness. Position recognition addresses the determination of the spatial orientation and location of components within a coordinate system this is essential for tasks like robotic pick-and-place operations and automated alignment. Completeness checks verify the presence and correct placement of all required components within an assembly, often as a prerequisite for subsequent process steps or product release. Shape and dimension checks focus on measuring geometric parameters to ensure adherence to specified tolerances, which is a critical aspect of dimensional quality control. Surface inspection evaluates the visual quality of surfaces either quantitatively such as roughness measurement or qualitatively, including defect detection like dents, scratches, or discoloration. The latter often employs machine learning techniques due to the subjective and complex nature of defining aesthetic defects.

In practical implementations, these inspection tasks frequently overlap, for example, a single system may simultaneously perform object identification and completeness verification. The integration of multiple vision tasks within a unified inspection system improves overall quality assurance by enabling more comprehensive and reliable product evaluations. Furthermore, the type of manufacturing process significantly influences how machine vision systems are designed and applied. Production can generally be classified into three main types mass production, batch production, and single-item production each presenting distinct requirements and constraints for vision system deployment in terms of flexibility, cycle time, and inspection resolution (Hornberg (2017).

Machine vision systems are extensively used in manufacturing environments to enhance quality control processes by enabling precise, automated inspection of products throughout various stages of production. These systems play a critical role in detecting defects, verifying dimensional accuracy, and ensuring compliance with established quality standards, thereby reducing the risk of defective products reaching the end of the production line. Their application leads to improved consistency, reduced human error, and greater operational efficiency. For example, in the tile and ceramic industry, machine vision technology is employed to inspect tiles for surface blemishes, color inconsistencies, edge irregularities, and cracks. By automating this inspection process, manufacturers can achieve higher throughput while maintaining stringent quality requirements (Anand, S. & Priya, L. 2019).

Summary

Machine vision applications in manufacturing can be categorized into six main functions: code recognition, object recognition, position recognition, completeness checks, shape and dimension checks, and surface inspection. These tasks often overlap in practice, enabling comprehensive product evaluations within unified systems . The type of production mass, batch, or single-item determines specific system requirements regarding flexibility, speed, and precision. Overall, machine vision enhances quality control by automating defect detection, verifying dimensions, and improving consistency and efficiency across industries such as tile and ceramic manufacturing (Anand & Priya, 2019).

4.6 Case Studies of Machine Vision in Manufacturing

To support the theoretical analysis and practical evaluation of AI-powered machine vision systems, this section presents two selected case studies from real-world applications. These cases were chosen for their direct relevance to industrial quality control and their demonstrated impact in production environments.

The first case study focuses on the Atlas Inspection System implemented by Volvo Cars. This example illustrates how AI-enhanced vision systems can significantly improve the detection of surface anomalies beyond human capabilities. It aligns closely with the context of automotive manufacturing and offers insights into integrating machine vision in complex assembly lines.

The second case study analyzes an AI-based system for the online detection of edge defects on inorganic solid materials. Although the industrial context differs from the automotive sector, the technical challenges such as defect localization, real-time processing, and precision classification are highly comparable. This case demonstrates the adaptability of AI vision systems in recognizing subtle edge anomalies, which is particularly relevant for inspecting structural components like vehicle doors or windshields.

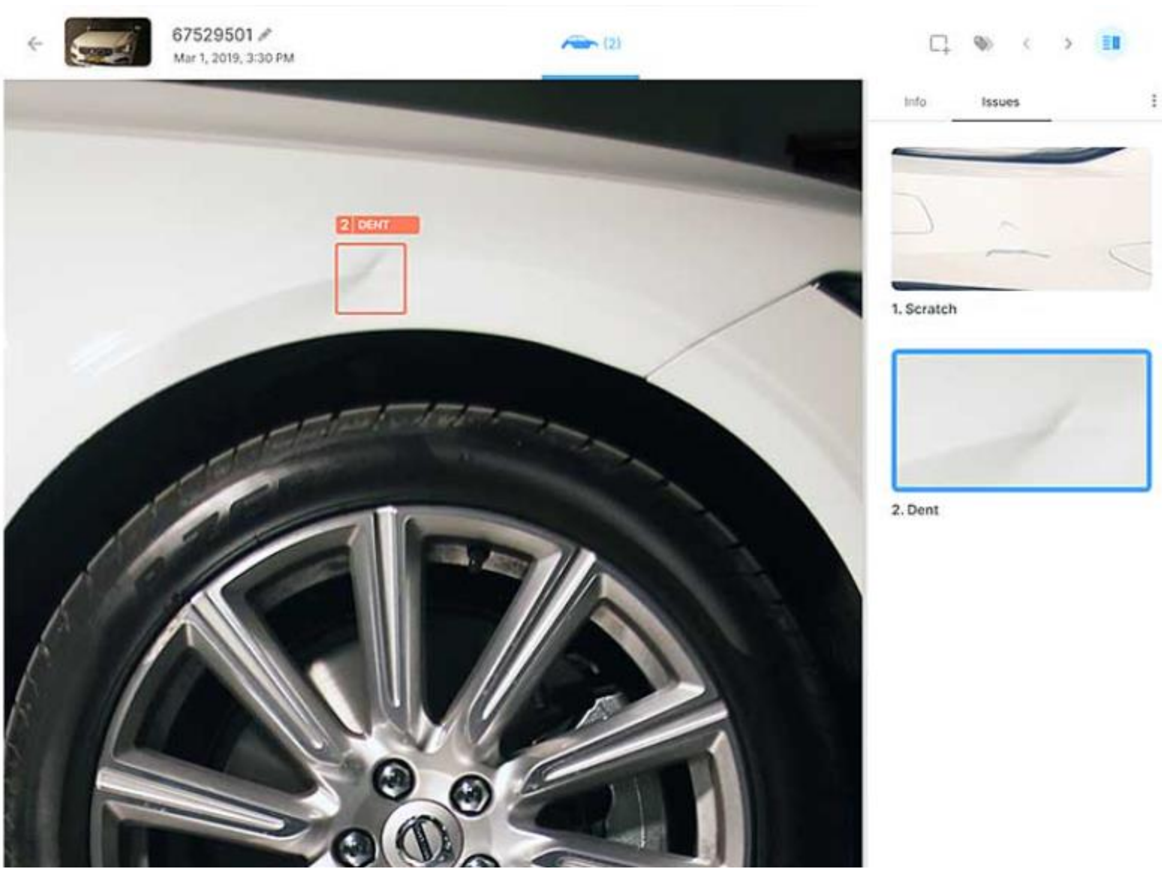
Together, these cases offer valuable evidence of how deep learning and vision technology can transform traditional inspection tasks, serving as benchmarks for evaluating the feasibility and benefits of similar applications at Valmet Automotive.

4.6.1 Case Study of Atlas Inspection System by Volvo Cars

The application of AI-based machine vision systems in automotive manufacturing has become increasingly prominent due to their superior efficiency and accuracy compared to traditional inspection methods. A notable example is the implementation of the Atlas inspection system by Volvo Cars at their manufacturing facility in Torslanda, Sweden, in collaboration with UVeye. The Atlas system employs multiple high-resolution cameras and sensors integrated within an aluminum tunnel structure, enabling a comprehensive 360-degree inspection of vehicles moving along an end-of-line conveyor. This advanced system identifies cosmetic defects, such as scratches and dents, down to 0.5 millimeters in diameter, within a mere 5 to 20 seconds per vehicle (Camillo, 2021).

Using artificial intelligence, the Atlas system is able to detect defects down to 0.5 millimeter in diameter anywhere on a moving vehicle. Photo Courtsy UVEYE

The Atlas system leverages deep learning algorithms within its AI engine, which rapidly processes approximately 10 gigabytes of visual data per vehicle. This data analysis occurs simultaneously onsite and via cloud servers, resulting in a detailed 3D model pinpointing precise locations of anomalies. Such automation significantly enhances the consistency and reliability of defect detection compared to manual inspections, which traditionally involve higher susceptibility to human error (Camillo, 2021).



Using artificial intelligence, the Atlas system is able to detect defects down to 0.5 millimeter in diameter anywhere on a moving vehicle. PHOTO COURTESY UVEYE

Table 4 illustrates Comparison of AI-Based Atlas Inspection vs. Manual Inspection

Table 4. Comparison of AI-Based Atlas Inspection vs. Manual Inspection adabpted from (Camillo, 2021).

Aspect	Atlas Inspection System	Manual Inspection
Inspection Time	5–20 seconds per vehicle	Several minutes per vehicle
Accuracy	~99,99%	Highly variable, prone to errors
Data Captured per Vehicle	Approximately 10 GB	Limited (subjective reporting)
Minimum Defect Size Detected	0,2–0,5 mm	Often misses micro-defects
Coverage	Complete 360-degree surface coverage	Partial, dependent on inspector
Data Processing	Automated AI analysis (real-time, cloud-based)	Manual visual judgment

(Camillo, 2021).

Volvo's experience mirrors broader industry trends, as multiple global automotive manufacturers, including Toyota, Skoda, Honda, and Daimler, have adopted or initiated pilot programs with Atlas. Reports from pilot implementations at two prominent German automakers indicated that the Atlas system uncovered between 10 to 40 percent more anomalies than human inspectors, effectively identifying paint chips and micro-scratches as small as 0,2 millimeters. These findings underscore the transformative potential of AI-based vision systems to enhance quality control significantly within automotive manufacturing contexts (Camillo, 2021).

Despite the clear advantages, certain limitations persist with the Atlas system. While its accuracy reaches near-perfect levels (approximately 99.99 percent), it currently inspects only exterior surfaces, unable to detect interior defects. Additionally, effective integration into existing assembly lines necessitates adjustments in workforce training and procedural changes, highlighting transitional challenges faced by companies adopting such advanced technologies. Nevertheless, OEMs have demonstrated substantial cost savings by detecting defects earlier and more consistently, thereby reinforcing the economic and operational viability of AI-based machine vision solutions in automotive quality assurance (Camillo, 2021).

Key Lessons for Valmet Automotive

Valmet Automotive should consider adopting full 360-degree inspection systems to achieve complete product coverage and invest in high-resolution imaging combined with real-time data processing to enhance defect detection precision.

Use High-Speed and High-Resolution Cameras: Faster cameras and better image quality mean more reliable detection even at high production speeds.

Combine Edge and Cloud Processing: Use a hybrid AI setup to process images quickly on-site (edge) and analyze trends centrally (cloud).

Start Defect Detection Earlier: Installing cameras earlier in the assembly process can help prevent rework and reduce defect-related costs later.

Prepare and Train Staff: Make sure employees are trained to work with the AI system, understand its outputs, and know how to react when issues are found.

Finally, Valmet Automotive must acknowledge current system limitations by combining AI exterior inspections with additional internal quality checks for a comprehensive quality assurance strategy.

The case study of the Atlas inspection system implemented by Volvo Cars highlights the transformative impact of AI-based machine vision technologies in automotive quality assurance.

Through the integration of high-resolution imaging, deep learning algorithms, and real-time cloud-based processing, the system achieves near-perfect detection rates for surface defects, with inspection times reduced to just a few seconds per vehicle.

Compared to traditional manual inspections, the Atlas system offers superior speed, accuracy, and comprehensive coverage, leading to earlier defect detection and significant cost savings.

While current limitations include a focus solely on exterior inspections and the need for procedural adjustments during integration, the overall findings strongly affirm the operational and economic advantages of adopting AI-driven vision systems in modern manufacturing environments.

4.6.2 Case Study of AI-Based Online Detection of Edge Defects on Inorganic Solid Material

This study El Mazgualdi et al. (2023) focuses on the application of Artificial Intelligence (AI), specifically Mask R-CNN deep learning architecture for real-time detection of edge defects (small chips and cracks) on moving sheets of inorganic solid materials, particularly safety glass.

The researchers addressed a critical challenge in Industry 4.0 manufacturing:

- Performing high-precision and real-time defect detection.

- Handling small datasets by using synthetic data augmentation.

- Achieving effective defect localization using a machine vision system fully integrated with a PLC for industrial automation.

Mask Region-Based Convolutional Neural Network (Mask R-CNN) is an advanced deep learning architecture that simultaneously performs object detection, classification, and instance segmentation. It identifies and localizes objects by drawing bounding boxes, assigns category labels to each object, and generates precise pixel-level masks outlining object boundaries. Extending the Faster R-CNN model, which detects objects only through bounding boxes, Mask R-CNN adds a segmentation branch, enabling detailed pixel-by-pixel object representation in addition to localization and classification.

Inspection System Overview

The developed system integrates hardware and software components into a real-time inspection platform. The main components include:

- A 64-megapixel CCD linear monochrome camera positioned above a conveyor
- A backlighting white LED bar to ensure consistent illumination
- A microcontroller-connected Programmable Logic Controller (PLC) to synchronize image acquisition and sorting decisions
- A Gigabit Ethernet network to transmit images to a control terminal for AI-based defect detection.

Once an image is captured upon triggering by a sensor, the Mask R-CNN model processes the image to detect edge defects. The decision is communicated back to the PLC, enabling automatic part sorting based on detected quality.

Data Acquisition and Annotation

A total of 132 images were captured from the inspection line. Defects were manually annotated using bounding boxes, focusing on detecting the presence rather than the precise shape of defects.

Due to the small number of real defect samples, synthetic defects were generated through data augmentation techniques. The final training dataset consisted of 50% real and 50% synthetic defects.

The dataset was split into a training set (100 images) and a validation set (32 images).

Results

The study by El Mazgualdi et al. (2023) demonstrated that AI-based vision systems, specifically using Mask R-CNN architectures, are capable of detecting small edge defects in moving glass sheets in real time.

Key findings include:

The Mask R-CNN model successfully detected and localized chip-type defects with acceptable accuracy, even under industrial constraints involving product movement.

The system achieved promising results despite a small and partially synthetic training dataset, proving the feasibility of using data augmentation techniques to compensate for limited real-world data.

The integration with a PLC and OPC UA communication enabled automated decision-making for product sorting based on detected defects.

The training phase showed stable convergence for object detection tasks (bounding box localization and classification) but limited precision in pixel-wise segmentation, mainly due to the use of bounding box annotations instead of exact contour masks.

Validation results indicated that model generalization was acceptable but would benefit significantly from improvements in dataset richness, class balance, and training duration.

The study concludes that while the AI-enhanced system performs well at a proof-of-concept level, further work is needed to ensure mass industrial deployment. Specifically, precise annotation methods, larger datasets, optimized training strategies, and real-time operational validation are critical next steps.

Key Lessons for Valmet Automotive

Precise Data Annotation: Valmet Automotive should move beyond bounding boxes and use pixel-level segmentation to improve AI defect detection, especially for critical components like paper machines and energy systems.

Improve Data Annotation Quality: Move from basic defect bounding boxes to pixel-level segmentation to improve AI classification accuracy, especially in detecting surface or form anomalies in doors and windshields.

Apply Data Augmentation Strategically: Use techniques such as synthetic defect generation and variation in lighting or angles to train AI models early, when real defect examples are few.

Ensure Industrial System Compatibility: Work with automation teams to ensure AI systems are compatible with existing PLCs and utilize standardized protocols like OPC UA for communication, avoiding delays in deployment.

Optimize for Real-Time Performance: Choose high-speed cameras and tailor lighting setups to match inspection points. Deploy faster AI inference engines that can meet takt time without compromising detection quality.

Pilot with Structured Testing: Before scaling, conduct pilots in actual production conditions using known defective and non-defective parts. Log key performance indicators such as detection rate, false positives, and missed defects. Use these findings to fine-tune model performance.

Prevent Overfitting in AI Models: Maintain diverse datasets with samples from various models and defect types. Apply cross-validation during training and use regularization to avoid overly narrow model behavior.

Develop a Stepwise Deployment Plan: Start with well-defined, high-value inspection areas (e.g., windshield or door stations). Use learnings from these pilots to gradually expand to other sections of the assembly line, adjusting models and setups as required.

Conclusion

The study conducted by El Mazgualdi et al. (2023) demonstrated the feasibility of implementing Artificial Intelligence-based computer vision systems for the real-time detection of small defects on moving inorganic solid materials, particularly safety glass.

By utilizing the Mask Region-Based Convolutional Neural Network (Mask R-CNN) architecture, the researchers successfully designed and validated a defect detection framework capable of identifying edge chips with acceptable accuracy under industrial conditions.

Despite the limited size of the real-world training dataset, the combination of high-resolution imaging, synthetic data augmentation, and deep learning techniques resulted in promising detection and localization outcomes.

The full integration of the machine vision system with industrial Programmable Logic Controllers (PLCs) through OPC UA communication further demonstrated the potential for seamless operational deployment in automated production environments.

However, the study also highlighted several areas requiring further improvement, including the need for precise pixel-level defect annotations, expansion and balancing of training datasets, additional model training and tuning, and real-time validation using live industrial data streams.

In conclusion, while the developed system achieved satisfactory performance as a proof of concept, additional enhancements are essential to ensure robust scalability, reliability, and real-time operational readiness for full industrial deployment.

5 Findings and Analysis (Confidential)

Classified

5.1 Vehicle Final Assembly (Confidential)

Classified

5.2 Challenges in Current Quality Control at Valmet Automotive (Confidential)

Classified

5.3 Cost-Benefit Analysis of Implementing a Machine Vision Tunnel (Confidential)

Classified

5.4 AI camera project at Valmet Automotive (Confidential)

Classified

5.4.1 AI Camera in Testing Phase in Innovation Center (Confidential)

Classified

5.4.2 Practical Evaluation of AI Camera Systems in Production Line (Confidential)

Classified

5.4.3 ROI Analysis with Sources – AI Camera Windshield (Confidential)

Classified

5.5 Quality Control of AI Camera Before vs. After (Confidential)

Classified

5.6 Questionnnaires and Interview (Confidential)

Classified

6 Conclusion

The final chapter of this thesis creates the key findings, financial implications, and practical outcomes of the research on AI-powered machine vision systems for automotive quality control. It repeats the core research questions, evaluates cost-effectiveness through return-on-investment analysis, and summarizes the main conclusions. Finally, it outlines several future research directions that could further advance the integration of intelligent visual inspection technologies in automotive manufacturing.

6.1 Research questions

This thesis investigated the potential of AI-powered machine vision systems to optimize quality control processes in automotive manufacturing. Four research questions guided the study:

1. **What are the most frequent quality issues observed in vehicle doors at Valmet Automotive, and which of these can be targeted through machine vision systems?**

Through quantitative analysis of historical defect data (2022–2024), the most common defects in vehicle doors were identified and prioritized based on their severity and suitability for detection by machine vision systems. These included surface anomalies such as scratches and dents, which are challenging to detect through manual inspection but are well suited for AI-based systems. These defects were prioritized by their occurrence rate, severity, and the potential impact on final product quality. The analysis revealed that surface defects particularly those involving visual irregularities are among the most common and severe issues. These types of defects are highly suitable for detection through AI-powered machine vision systems, as they can be identified reliably using high-resolution imaging and automated recognition algorithms. By mapping defect categories to machine vision capabilities, the study confirms that such systems offer a viable solution for addressing the most critical quality issues in door assembly.

2. **How suitable is AI-based machine vision, particularly vision tunnels, for detecting door-related defects?**

The evaluation of AI-based machine vision systems, particularly vision tunnels, highlights their strong suitability for detecting door-related defects in automotive manufacturing environments. This assessment was carried out using a case-based approach, primarily analyzing the Atlas Inspection System implemented by Volvo Cars. This system, developed in collaboration with UVeye, consists of a tunnel-like structure equipped with multiple high-resolution cameras and integrated AI-driven software capable of conducting a full 360-degree vehicle inspection.

The system's capabilities include the real-time detection of surface defects such as scratches, dents, and misaligned components down to 0.2–0.5 mm in size. It operates at high inspection speeds, requiring only 5–20 seconds per vehicle, which aligns well with the takt times in high-volume assembly lines. These features illustrate the technical feasibility of deploying such systems in pre-final-assembly inspection points, particularly for components like vehicle doors that often show critical surface anomalies requiring rapid detection.

In addition to detection capabilities, the system supports operational integration through real-time data processing and defect visualization via cloud and local servers. This ensures traceability and provides immediate feedback to production teams. Furthermore, the system enables the generation of detailed inspection reports and image documentation for each vehicle, thus facilitating data-driven quality management.

Although Valmet Automotive has not yet implemented a vision tunnel system for door inspection, the findings from the Volvo case study provide strong indications that such technology is suitable for integration into the company's operations. This suitability is reinforced by the nature of the most frequent door defects identified in Valmet Automotive's internal data, many of which are visual in nature and can be reliably detected by high-resolution machine vision setups. However, the deployment of such systems requires careful planning concerning investment costs, line modifications, and staff training to achieve full operational benefits. Therefore, the case-based evaluation confirms that vision tunnels are not only technically capable but also operationally compatible with automotive quality inspection processes, offering significant improvements in speed, accuracy, and data traceability compared to traditional manual inspection methods.

3. **What is the potential operational and financial impact of deploying a machine vision tunnel at the door inspection station?**

The operational and financial impact of deploying a machine vision tunnel at the door inspection station has been assessed through a feasibility study grounded in quantitative analysis of internal defect data (2022–2024) and benchmarked investment and labor cost estimates. This analysis aimed to determine whether such an automated solution could justify its cost through operational improvements and measurable financial returns.

From an operational perspective, machine vision tunnel systems offer distinct advantages. They enable high-resolution, automated inspection of surface defects such as scratches, dents, and misalignments with a consistency and speed that far surpasses manual methods. Such systems support round-the-clock inspection without fatigue, offer traceable defect documentation, and contribute to standardizing inspection results across production shifts. These capabilities align with Valmet Automotive's objective to enhance quality assurance reliability and reduce human dependency in repetitive tasks.

Financially, however, the results are less favorable in the short term. The cost-benefit analysis, based on current repair times and defect rates at Valmet Automotive, revealed that the payback period for the machine vision tunnel system would range between 10 and 15 years, depending on operational scenarios and production volumes. This extended return horizon is primarily attributed to the relatively low volume of vehicle units produced, which limits the scale of defect-related savings that can be accumulated annually. While labor cost reductions and rework avoidance contribute to financial gains, the high capital investment required for the tunnel setup including infrastructure, cameras, lighting, and system integration reduces the profits in the short and medium term.

In conclusion, although machine vision tunnels hold strong operational promise, their financial feasibility under current production volumes is limited. The long payback period suggests that the investment would be more justifiable in high-throughput environments or in future scenarios where production volume increases. Alternatively, intermediate solutions such as AI-powered single-camera systems or semi-tunnel configurations may offer more practical value in the near term.

4. **How does the AI-based camera system at the windshield station perform in terms of defect detection accuracy, operational efficiency, and technical limitations?**

The evaluation of the AI-based camera system implemented at the windshield inspection station offered valuable insights into its real-world performance, particularly in terms of defect detection accuracy, operational efficiency, and technical limitations. During the testing phase and subsequent full deployment, the system proved highly effective in identifying surface anomalies on windshields, thereby supporting real-time defect prevention and reducing reliance on manual inspection. Functionally, the AI camera demonstrated consistent accuracy in detecting visible defects under controlled conditions and delivered operational benefits such as automated defect documentation, shorter inspection cycles, and traceable image-based feedback. These capabilities aligned with quality assurance objectives and contributed to process reliability on the production line.

From a financial standpoint, the system achieved a payback period of approximately one year, making it a cost-effective solution for targeted defect detection. The investment was justified through avoided rework and improved inspection efficiency, confirming the system's economic viability for focused quality control tasks. However, the real-line deployment also revealed notable challenges. These included environmental factors such as lighting reflections, inconsistent part positioning, and production-related disturbances, all of which occasionally reduced the reliability of detection. These limitations highlight the importance of stable operating conditions and system calibration for maintaining optimal performance.

Overall, the case of the AI camera project supports the view that standalone AI-based machine vision solutions can deliver measurable benefits when integrated into defined stages of the production line. The findings demonstrate both the adaptability and the practical constraints of such systems, contributing to a more nuanced understanding of their role in enhancing quality control processes at Valmet Automotive.

6.2 Cost and Return on Investment

The financial assessment conducted in this thesis confirms the economic viability of AI-powered machine vision systems for quality control in automotive manufacturing. Two implementation scenarios were evaluated: a standalone AI camera system currently deployed at the windshield inspection station, and a full-scale machine vision tunnel proposed for door inspections.

For the AI camera system, the return on investment was achieved within one year, driven by direct reductions in defect-related rework and enhanced inspection efficiency. The system's rapid payback period and low initial cost make it a practical solution for targeted quality control applications, particularly when focused on specific defect types at defined inspection points.

In contrast, the vision tunnel system involves a significantly higher investment and infrastructure adaptation. Based on internal defect data, repair times, and modeled savings, the estimated payback period was calculated to fall between 10 and 15 years. This extended timeframe is primarily due to the relatively low volume of units produced and the high upfront capital cost. This reduces the financial attractiveness of the investment in the early years , the tunnel's broader coverage and automation potential still offer long-term strategic value through improved consistency, reduced inspection variability, and enhanced product quality.

Together, these findings suggest that while standalone AI systems provide immediate operational gains with low financial risk, tunnel-based solutions represent a longer-term investment strategy suited for high-throughput environments with stable production volumes and complex quality requirements.

6.3 Final Summary

Although traditional quality control methods are dependable, they often fall short in meeting the high-speed and precision requirements of modern automotive production lines. This thesis has demonstrated that AI-driven machine vision systems offer a practical and effective alternative. These systems improve defect detection accuracy, reduce manual labor, enhance traceability, and enable real-time quality assurance.

Through a combination of quantitative defect data analysis, industry case studies, structured questionnaires, and an on-site evaluation of the AI camera system at Valmet Automotive, this research illustrates the tangible benefits of transitioning from manual to automated visual inspection. The findings confirm that machine vision technology can substantially improve quality performance and process reliability.

While vision tunnel systems offer comprehensive inspection coverage and superior defect detection capabilities, their implementation is associated with high investment costs and requires significant integration efforts. In contrast, the AI camera system currently deployed at the windshield inspection station provided a cost-effective and scalable example of real-time defect detection. It also revealed practical limitations, such as sensitivity to environmental conditions and variability in part positioning, which must be addressed to ensure broader system reliability.

In summary, this study highlights the growing potential of AI-based visual inspection technologies in automotive manufacturing and offers practical recommendations for their integration. It supports the view that AI-powered quality control is a feasible and strategically valuable path forward.

6.4 Future Research Directions

Future research could explore the following areas:

- Comparative benchmarking of multiple machine vision vendors and system architectures: Conduct side-by-side testing of leading vision systems under controlled factory conditions to identify the best-performing solutions in terms of accuracy, integration ease, and cost-efficiency.

- Integration of internal and external inspection systems for comprehensive quality monitoring: Develop a unified data infrastructure where early-stage (in-line) inspections such as glue trace checks, component presence, or part alignment are automatically linked with final inspection results from end-of-line vision tunnels.

This would allow Valmet Automotive to trace defects back to specific production stages, improving root-cause analysis and enabling predictive quality controls.

- Exploration of machine vision applications for interior defects or hidden component verification: Investigate the use of specialized vision systems such as borescopes or 3D laser triangulation to inspect components inside doors, dashboards, or other enclosed modules, which are typically excluded from current surface-based inspections.

- Investigation into the feasibility and implementation of a full vehicle body machine vision tunnel: Assess how a multi-camera tunnel system can be integrated into the existing assembly line to inspect paint, panel gaps, surface damage, and assembly accuracy across the entire vehicle body without stopping the line.

These directions would deepen understanding of machine vision’s broader applicability and help refine implementation strategies for the automotive sector and beyond.

References

Abdelhamed, H., Ibrahim, H., & Wang, Q. J. (2019). Automatic paint defect inspection using deep learning-based systems. Robotics and Computer-Integrated Manufacturing, 56, 93-104.

Alkan, B., Vera, D. A., Ahmad, M., Ahmad, B., & Harrison, R. (2018). Complexity in manufacturing systems and quality management: A review and future research agenda. International Journal of Production Research, 56(1-2), 399-424.

Abdelhamed, A., et al. (2019). Automotive Paint Defects: A Review. Journal of Automotive Engineering, 11(2), 43-52.

Anand, S., & Priya, L. (2019). A guide for machine vision in quality control. Chapman and Hall/CRC.

Antony, J., & Kaye, M. (1995). Experimental quality: A strategic approach to achieve and improve quality. Chapman & Hall.

Antony, J., et al. (1998). Design of Experiments and Taguchi Methods: Implementation barriers. International Journal of Quality & Reliability Management.

Arora, V. (2025). Managing Quality Costs: Strategic Approaches and Best Practices. Quality Management Journal.

Assembly Magazine. (2022). Enhancing Quality Control with AI-powered Vision Tunnels. Retrieved from: https://www.assemblymag.com/articles/96507-volvo-enhances-quality-control-with-ai-powered-vision-tunnels

Bhattacharyya, S., & Smith, D. (2018). Advances in automotive glazing technologies: Performance, safety, and aesthetics. Journal of Automobile Engineering, 232(14), 1920-1934.

Biswas, P. (2021). Quality Inspection Procedures and Best Practices. Retrieved from https://preteshbiswas.com/2021/02/quality-inspection-procedures-and-best-practices/

Brown, R., & Wang, S. (2021). Automating Quality Control Based on Machine Vision Towards Automotive 4.0. In Advances in Manufacturing Technology XXXIV (pp. 123-130). Springer. https://link.springer.com/chapter/10.1007/978-3-031-16407-1_16

Breyfogle, F. W., & Cupello, J. M. (2001). Managing Six Sigma. Wiley.

Camillo, J. (2021, January 7). AI-based vision technology aids vehicle inspection. Assembly Magazine. Retrieved from https://www.assemblymag.com/articles/96075-ai-based-vision-technology-aids-vehicle-inspection

Cognex Corporation. (2024). Machine Vision. Retrieved April 10, 2025, from https://www.cognex.com/en-fi/products/machine-vision

Chung, I. S. (2008). Apparatus for inspecting vehicle window.

Chung, Y. K., & Kim, K. H. (1998). Automated visual inspection system of automobile doors and windows using the adaptive feature extraction. International Conference on Knowledge-Based and Intelligent Information and Engineering Systems, 3, 286–293.

CT Engineering Group, 2024 – Insights on camera technologies in automotive, highlighting the emerging role of hyperspectral imaging and its challenges. https://www.ctengineeringgroup.com/revolutionising-the-automotive-industry-with-machine-vision/ (Accessed, 4.2025)

Cui, A., Zhang, C., He, D., & Chen, X. (2011). Research on device and method of vision inspection of a vehicle dashboard framework. IEEE International Conference on Electronic Measurement & Instruments, 4, 150–154.

Dale, B. G., et al. (2003). Managing Quality. Blackwell Publishing.

Davies, E. 2012. Computer and Machine Vision. 4th edition. Waltham: Academic Press.

De Souza Silva, C.A. & Paladini, E.P. (2025). "Smart Machine Vision System to Improve Decision-Making on the Assembly Line." Machines, 13(2): 98.

De Feo, J. (2017). Juran's Quality Handbook: The Complete Guide to Performance Excellence (7th ed.). McGraw-Hill. https://www.amazon.com/Jurans-Quality-Handbook-Performance-Excellence/dp/1259643611/

Diffraction Limited. (2021). CCD vs CMOS: Understanding the Differences Between Two Key Image Sensor Technologies. Retrieved from https://diffractionlimited.com/wp-content/uploads/2021/06/eBook-CCD-vs-CMOS.pdf

Duarte, J. (2023). Cost of Quality: Analysis and Improvement Strategies. Journal of Operational Excellence.

Elahi, M., Afolaranmi, S. O., Lastra, M., & Pérez, A. (2023). A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. Discover Artificial Intelligence, 3(1). https://doi.org/10.1007/s44163-023-00089-x

El Mazgualdi, C., Masrour, T., El Hassani, I., Barka, N., & Khdoudi, A. (2023). Artificial Intelligence for Product Quality Inspection in Manufacturing Industry: Online Detection of Edge Defects on Inorganic Solid Material. https://doi.org/10.21203/rs.3.rs-2586790/v1

Frustaci, F., Spagnolo, F., Perri, S., Cocorullo, G., & Corsonello, P. (2022). "Robust and High-Performance Machine Vision System for Automatic Quality Inspection in Assembly Processes." Sensors, 22(8): 2839.

Gardiner, L. R., & Mitra, A. (1994). Quality control methodologies in service industries. International Journal of Quality & Reliability Management.

Goetsch, D. L., & Davis, S. (2021). Quality Management for Organizational Excellence: Introduction to Total Quality (9th ed.). Pearson.

Golnabi, H., & Asadpour, A. (2007). Design and application of industrial machine vision systems. Robotics and Computer-Integrated Manufacturing, 23(6), 630–637. https://doi.org/10.1016/j.rcim.2007.02.005

Google Cloud. (2023). Artificial intelligence defined. https://cloud.google.com/learn/what-is-artificial-intelligence

Green, D., et al. (2021). Lean Manufacturing and Quality Assurance in Industry 4.0. IEEE Transactions on Manufacturing.

Green, D., & Smith, J. (2021). Artificial Intelligence for Product Quality Inspection toward Smart Industries: Quality Control of Vehicle Non-Conformities. IEEE Access, 8, 123456-123467. https://ieeexplore.ieee.org/document/9080396

Gu, X., Jin, X., Ni, J., & Koren, Y. (2016). Manufacturing process control based on integrated gap and flushness sensing. CIRP Annals-Manufacturing Technology, 65(1), 417-420.

Gupta, M., & Campbell, V. (1995). The Cost of Quality. ASQC Quality Press.

Hairulliza, M. J., et al. (2005). Statistical process control in manufacturing industries. Journal of Quality in Maintenance Engineering.

Harish. (2015, October 11). 100% visual inspection – being human. Harish's Notebook. https://harishsnotebook.wordpress.com/2015/10/11/100-visual-inspection-being-human/

Harrington, H. J. (1999). Performance Improvement: A Total Poor-Quality Cost System. McGraw-Hill.

Hidayat, A. A., Almahdy, I., Firdaus, A., Kholil, M., Haekal, J., Widodo, T., & Rukmayadi, D. (2024). Quality Control Analysis of Piston Gasoline Products using the DMAIC Approach. International Journal of Scientific and Research Publications (SRS Prints), 4(1), 09-16.

Hoang, M. L. (2024). Current State, Challenges, and Data Processing of AI in Sensors and Computer Vision. 1–18.

Hong, Y., Jung, M., Kim, J., & Yoon, S. (2018). Quality inspection system for automotive assemblies using 3D vision and machine learning. International Journal of Precision Engineering and Manufacturing, 19, 577-585.

Hong, H., et al. (2018). Quality Control Techniques for Automotive Industry: An Overview. Quality Magazine, 25(7), 34-41.

Hornberg, A. (Ed.). (2017). Handbook of machine and computer vision : The guide for developers and users. John Wiley & Sons, Incorporated.

Huber, C., Knoll, D., & Guthe, M. Fully-Synthetic Training for Visual Quality Inspection in Automotive Production. https://doi.org/10.48550/arxiv.2503.09354

International Organisation for standardization (ISO). (2015). ISO 9001:2015 Qaulity Manegement Requirements. ISO. Retrieved from https://www.iso.org/standard/62085.html

Islam, M.R., Zamil, M.Z.H., Rayed, E., Kabir, M.M., Mridha, M.F., Nishimura, S., & Shin, J. (2024). "Deep Learning and Computer Vision Techniques for Enhanced Quality Control in Manufacturing Processes." IEEE Access, 12, 1–31.

Javaid, M., Haleem, A., Singh, R.P., Rab, S., & Suman, R. (2022). "Exploring impact and features of Machine Vision for progressive Industry 4.0 culture.

Johnson & Kumar (2022). AI Integration in Manufacturing: A Comprehensive Review.

Johnson, M., & Lee, B. (2019). Q-EYE TUNNEL: A Novel Inspection System Based on Artificial Vision and Light Pattern Projections for Detecting Defects on Car Bodies. Proceedings of the European Automotive Congress, 64, 1-10.

Johnson, A., & Aronsson, H. (2020). Automated visual inspections for final assembly: A case study of cab assembly at Scania Oskarshamn.

Juran Institute, "The 1-10-100 Rule": https://www.juran.com/blog/the-1-10-100-rule/

Juran, J. M., & Gryna, F. M. (2021). Juran's Quality Handbook (7th ed.). McGraw-Hill Education.

Jones, P., & Patel, R. (2020). Automation of Quality Control in the Automotive Industry Using Deep Learning Algorithms. IEEE Transactions on Industrial Informatics, 17(3), 1234-1242. https://ieeexplore.ieee.org/document/9349273

Konica Minolta Sensing – EINES Vision Systems brochure, detailing capabilities of automotive inspection tunnels (gap & flush, paint defect detection). https://sensing.konicaminolta.eu/mien/products/gloss-and-appearance-measurement/appearance-meter/eines-vision-systems-solutions (Accessed, 4.2025)

Kropik, M. (2021). Produktionsleitsysteme für die Automobilindustrie (Vol. 166, No. 11). Berlin, Heidelberg: Springer Berlin Heidelberg.

Kwon, S. Y., & Lee, M. Y. (2016). Inspection device for vehicle door.

Lu, E. (2013). Fluorescence image detection device for coating of sealing element of automobile.

Mahmood, S., & Kureshi, N. I. (2015). Cost of Poor Quality: A Framework for Improvement. Total Quality Management & Business Excellence, 26(7-8), 1-13.

Mahanti, R., & Antony, J. (2005). Six sigma in software development. Journal of Quality Assurance Institute.

Maximl. (2021). The 1-10-100 rule to enhance the quality of your products and help you detect defects earlier. https://maximl.com/blog/digital-transformation/the-1-10-100-rule-to-enhance-the-quality-of-your-products-and-help-you-detect-defects-earlier/

Meissner, W. (1978). Door checking device, in particular for vehicle doors. https://patents.google.com/patent/EP0002175A1/en

Michalos, G., Makris, S., Mourtzis, D., & Chryssolouris, G. (2012). An intelligent search algorithm-based method to derive assembly line design alternatives. International Journal of Computer Integrated Manufacturing, 25(3), 211-229.

Michalos, G., et al. (2012). Automotive Door Assembly Inspection: Methods and Technologies. Robotics and Computer-Integrated Manufacturing, 28(2), 147-155.

National Highway Traffic Safety Administration (NHTSA): www.nhtsa.gov (accessed, 4.2025)

Nenadál et al. (2018). Principles of Quality Management. CRC Press.

Nunner, F., & Stephan, H. (2006). Method and device to check the gap between a vehicle body and doors or lids attached thereto. https://www.freepatentsonline.com/EP1671876.html

Oakland, J. S. (2020). Oakland on Quality Management (4th ed.). Routledge.

Oakland, J. S. (2003). Statistical Process Control (5th ed.). Butterworth-Heinemann.

Pandharipande, A., Cheng, C.-H., Dauwels, J., Gurbuz, S. Z., Li, G., Piazzoni, A., Wang, P., & Santra, A. (2023). Sensing and Machine Learning for Automotive Perception: A Review. IEEE Sensors Journal, 23, 11097–11115.

Paturi, U. M. R., & Cheruku, S. (2021). Application and performance of machine learning techniques in manufacturing sector from the past two decades: A review. Materials Today: Proceedings, 38, 2392–2401.

Pérez, L., Rodríguez, Í., Rodríguez, N., Usamentiaga, R., & García, D. F. (2016). Robot guidance using machine vision techniques in industrial environments: A comparative review. Sensors, 16(3), 335. https://doi.org/10.3390/s16030335

Petty, R. (1997). Managing the Hidden Costs of Quality. Quality Progress, 30(10), 45-49.

Photoneo, (2023). Machine vision systems – Industry applications & cost implications. From https://www.photoneo.com/machine-vision-systems-industry-applications-cost-implications/ (accessed 4.2025)

"Precision Door Assembly Practices in Automotive Manufacturing," Assembly Magazine. https://www.assemblymag.com/articles/96974-precision-door-assembly-practices-in-automotive-manufacturing

Rodriguez et al. (2020). Automation and Technological Integration in Industrial Manufacturing.

Rosiawan, M., Singgih, L.M., Widogo, E. (2019). Model of quality costs and economic benefits of a business process of manufacturing companies. https://doi.org/10.1080/23311916.2019.1678228

Silva, R. L., Rudek, M., Szejka, A. L., & Junior, O. C. (2018). Machine vision systems for industrial quality control inspections. In Product Lifecycle Management to Support Industry 4.0: 15th IFIP WG 5.1 International Conference, PLM 2018, Turin, Italy, July 2–4, 2018, Proceedings 15 (pp. 631–641). Springer International Publishing. https://doi.org/10.1007/978-3-030-01614-2_58

Slattery, R. (2005). Quality control in non-manufacturing sectors. Quality Progress.

Smith, J., & Lee, A. (2020). State of the Art in Defect Detection Based on Machine Vision. International Journal of Precision Engineering and Manufacturing-Green Technology, 7(4), 703-717.

Smith, A., & Brown, B. (2020). The Evolution of Quality Control in Advanced Manufacturing Systems. Journal of Industrial Processes.

Soderborg, N. R., & May, G. S. (2010). In-line inspection techniques for defect detection in manufacturing processes. IEEE Transactions on Semiconductor Manufacturing, 23(1), 72-79.

Suryawanshi, R. K., & Singh, S. (2024). Artificial Intelligence and Its Applications. International Journal of Advanced Research in Science, Communication and Technology, 654–660.

Tan, W. (2019). Device for inspecting automobile door hinge parts by photographic identification.

Trivedi, D. (2024, January 16). AI-powered scanners or fixed cameras for vehicle inspections. Inspektlabs. Retrieved from https://inspektlabs.com/blog/ai-powered-inspection-scanners-or-fixed-cameras-for-vehicle-inspections/ (accessed, 4.2025)

Tzampazaki, M., Zografos, C., Vrochidou, E., & Papakostas, G.A. (2024). “Machine Vision—Moving from Industry 4.0 to Industry 5.0.” Applied Sciences, 14(4): 1471.

"Using Quality Gates to Improve Automotive Production," Quality Magazine. https://www.qualitymag.com/articles/95396-using-quality-gates-to-improve-automotive-production

UVeye. (2022, June 24). GM Funds Development of UVeye Inspection Technology. Retrieved from https://www.uveye.com

Vergara-Villegas, O. O., Cruz-Sánchez, V. G., de Jesús Ochoa-Domínguez, H., de Jesús Nandayapa-Alfaro, M., & Flores-Abad, Á. (2014). Automatic Product Quality Inspection Using Computer Vision Systems. In Lean Manufacturing in the Developing World (pp. 135–156). Springer, Cham. https://doi.org/10.1007/978-3-319-04951-9_7

Vision Systems Design, 2020 – BMW Steyr plant pilot of Inspekto S70 AI vision system, detecting an improperly locked knock sensor with minimal setup https://www.vision-systems.com/factory/article/14185700/bmw-factory-deploys-machine-vision-system-inspekto-s70 (Accessed, 4.2025)

Wang, L., & Chen, Y. (2015). Visual inspection system for automobile parts.

Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems, [in press]. https://doi.org/10.1016/j.jmsy.2018.01.003

Wang, L., & Green, D. (2022). An Automatic Surface Defect Inspection System for Automobiles Using Machine Vision Methods. Sensors, 19(3), 644. https://www.mdpi.com/1424-8220/19/3/644

Wheeler, J., Amman, S. A., & Whitens, M. J. (2020). In situ vibration-based verification of vehicle doors.

Wood, D. C. (Ed.). (2012). Principles of quality costs: financial measures for strategic implementation of quality management. Quality Press.

Wood, D. 2015. Principles of Quality Costs: Financial Measures for Strategic Implementation of Quality Management. ASQ Quality Press.

Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. Production & Manufacturing Research, 4 (1), 23–45.

Xie, M., & Goh, T. N. (1999). Statistical Techniques in Quality Control. World Scientific.

Zebra Technologies (2023), Automotive Machine Vision Guide – Descriptions of vision applications in frame/body assembly. https://manuals.plus/zebra/iris-gtx-vision-solutions-machine-manual (accessed, 4.2025)

Zhang & Lee, (2023). Real-Time Defect Detection Using AI Cameras in Manufacturing" in Robotics and Computer-Integrated Manufacturing.

Zhang, H., & Lee, S. (2023). Comparative Analysis of AI-driven Quality Inspection Techniques in Vehicle Manufacturing. Journal of Manufacturing Systems, 69, 432-444.