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Application of machine vision and AI in general assembly manufacturing

Department of Mechanical and Materials Engineering
Master's thesis

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Master's thesis

Subject: Design and TCO-based profitability calculation for identified machine vision systems.

Case: Valmet Automotive's general assembly

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Title: Application of machine vision and AI in general assembly manufacturing

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The demand for cost-efficient and consistent quality control and automation has increased significantly in the highly competitive automotive industry, which has accelerated interest in the application of machine vision and artificial intelligence (AI) in general assembly processes. However, identifying suitable applications and designing machine vision systems remains a complex challenge. This study develops a systematic literature-based machine vision design approach and a total cost of ownership (TCO)-based profitability calculation method for the economic evaluation of machine vision systems. The frameworks are based on a comprehensive literature review, which identifies key design principles and considerations for machine vision system design and TCO-based profitability calculations. The developed design approach is applied in the design of machine vision systems for Valmet Automotive's general assembly operations. The applications for the designed machine vision systems are based on interviews with Valmet Automotive personnel and research on state-of-the-art machine vision solutions. The TCO-based profitability calculations of the designed machine vision systems identify the processes of automotive manufacturing general assembly that benefit the most from machine vision implementation in the case of Valmet Automotive. This study contributes to the growing adoption of machine vision and AI in manufacturing by combining technical machine vision design considerations with economic evaluation, as well as providing insights into potential applications for machine vision systems.

Keywords: machine vision, artificial intelligence, quality control, profitability calculation, general assembly, automotive manufacturing

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Kysyntä kustannustehokkaalle laadunvalvonnalle ja automaatiolle on lähiaikoina kasvanut merkittävästi erittäin kilpailussa autoteollisuudessa. Tämä on lisännyt kiinnostusta konenäön ja tekoälyn käyttöön kokoonpanon prosesseissa. Mahdollisten konenäön käyttökohteiden tunnistaminen ja konenäköjärjestelmien suunnittelu on kuitenkin haastavaa. Tässä tutkimuksessa kehitetään systemaattinen konenäön suunnittelumenetelmä sekä elinkaarikustannuksiin perustuva konenäköjärjestelmien kannattavuuslaskentamenetelmä. Menetelmät pohjautuvat kattavaan kirjallisuuskatsaukseen, jossa tunnistetaan keskeiset suunnitteluperiaatteet ja huomioon otettavat tekijät sekä konenäköjärjestelmien suunnittelussa että kannattavuuslaskennassa. Kehitettyä suunnittelumallia sovelletaan Valmet Automotiven kokoonpanon konenäköjärjestelmien suunnitteluun ja havaitut konenäköjärjestelmien käyttökohteet perustuvat Valmet Automotiven henkilöstön haastatteluihin sekä edistyksellisten konenäköratkaisujen kirjallisuuskatsaukseen. Suunniteltujen konenäköjärjestelmien kannattavuuslaskelmat osoittavat, mitkä autoteollisuuden kokoonpanon prosessit hyötyisivät eniten konenäön käyttöönotosta Valmet Automotiven tapauksessa. Tutkimus edistää konenäön ja tekoälyn kasvavaa hyödyntämistä valmistavassa teollisuudessa yhdistämällä teknisen suunnittelun ja kannattavuuslaskennan sekä osoittamalla näkemyksiä potentiaalisista konenäköjärjestelmien käyttökohteista.

Avainsanat: konenäkö, tekoäly, laadunvalvonta, kannattavuuslaskenta, kokoonpano, autoteollisuus

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1 Introduction

The demand for cost-efficient and consistent quality control and automation has increased significantly in the highly competitive automotive industry [1]. The introduction of artificial intelligence (AI)-based machine vision cameras has expanded the possibilities of implementing machine vision for such applications [2]. Identifying potential applications for machine vision systems is an ongoing process in the manufacturing industry, as the full potential of machine vision has yet to be explored [3]. Additionally, designing such systems remains a complex challenge that involves balancing technical requirements, practical feasibility, and economic considerations [4]. Existing machine vision design approaches provide valuable insights into aspects of design, but they are often fragmented, rarely account for profitability in decision-making and frequently rely on suppliers to translate requirements into solutions [3]. While suppliers possess strong expertise and can offer excellent support, relying solely on them can lead to suboptimal cost efficiency, vendor lock-in, and reduced internal know-how [5].

This study addresses challenges regarding machine vision design and profitability calculation, while also providing insights into potential machine vision applications. Machine vision system and equipment design literature is used to provide design principles and equations for a systematic machine vision design approach. Total cost of ownership (TCO) and engineering economics literature is used to provide profitability calculation principles and equations for a systematic TCO-based machine vision system profitability calculation approach. Research on industrial machine vision solutions provides insights into the feasibility and design of advanced and complex machine vision solutions. Interviews with Valmet Automotive personnel are used to identify potential machine vision applications in Valmet Automotive's general assembly. The systematic machine vision design and TCO-based profitability calculation approaches are applied in evaluating machine vision applications at Valmet Automotive. The results of the designs and TCO-based profitability calculations provide the processes that would benefit the most from machine vision implementation. This study aims to answer the following research questions:

- Which processes in the automotive manufacturing general assembly would benefit most from machine vision implementation?

- How can cross-domain design principles be applied to systematically design machine vision systems?
- How can TCO-based profitability calculation methods be applied to evaluate the costs and profitability of machine vision systems?

The thesis is structured as follows: Chapter 2 presents a literature-based approach to machine vision system design and profitability calculation, as well as research on machine vision solutions in the industry; Chapter 3 describes the methodology for machine vision application evaluation, including interviews, system design and TCO-based profitability calculations for the selected applications; Chapter 4 presents the results of the application evaluation, summarizing technical and economic findings of the designed applications and the TCO-based profitability calculations; Chapter 5 provides the conclusions of the thesis.

2 Literature review

This chapter presents a systematic literature-based approach to machine vision system design and profitability calculation, as well as research on industrial machine vision solutions. The machine vision design approach is based on machine vision system and equipment design literature, and the TCO-based profitability calculation method is based on TCO and engineering economics literature. The research on machine vision solutions includes solutions found in literature, offered by suppliers, and implemented by other manufacturers. Together the literature review establishes a systematic approach to machine vision design and profitability calculation and provides insights into the feasibility and design of advanced machine vision solutions.

2.1 Machine vision design and profitability calculation

The project sequence for machine vision system implementation begins with system specification, which forms the foundation for a successful design. This is followed by the design of the machine vision system, covering key aspects such as determining the field of view and working distance, selecting the camera, lens and illumination, designing system-specific equipment such as robotics, and designing the mechanical and electrical aspects of the system. Once the design is complete, the system costs can be evaluated, and the TCO-based profitability calculations can be performed. If the calculations indicate profitability and management approves the project, implementation can begin. The implementation project starts with a kick-off meeting, followed by testing, finalizing system design, procurement of equipment and spare parts, hardware installation, PLC integration, camera software setup, final test runs, maintenance planning, and personnel training. Once the system is verified to be fully operational and all documentation is complete, the project can be concluded with a handover to production. The machine vision project should be documented in written form, such as the literature-based system specification list in Appendix 1, system design list in Appendix 2, and TCO-based profitability calculation list in Appendix 3, as well as system instructions, maintenance plans, mechanical drawings, circuit diagrams, and component handbooks [4].

2.1.1 System specification

Comprehensive and detailed system specification is essential, as insufficient specification can lead to significant issues in the later phases of a machine vision project. The system specification should include task information, expected benefits, time requirements, part information, part presentation, and environment. The task information and expected benefit section should provide a clear description of the objectives that the machine vision system is intended to achieve. Additionally, the expected benefits should be outlined, such as cost savings, improved quality or increased data for process optimization. Further key information regarding the task and benefit includes the size of the smallest feature to be detected and the required system accuracy. The time requirements, such as maximum processing time, processing time variability, and time from inspection to result, are also essential information in defining the expectations and limitations of the machine vision system [4].

A precise description of the part is essential, including key features, dimensional tolerances, color variations, and surface finish. It should also be specified whether there are any additional visual characteristics such as oil films, adhesives, corrosion, labels, or fingerprints. To collect this information, technical drawings and CAD models provide excellent sources of detailed data on dimensions and key features of the product. Part presentation should also be clearly defined, including positioning tolerances in both axial and rotational directions, positioning method, and the number of parts within the field of view. Another critical aspect of part presentation is whether the part is continuously moving or stationary during the inspection. In this context, either the line speed for a continuously moving part or the duration of no movement for a stationary part should be specified [4].

Machine vision systems can include user interfaces within their environment, for example to visualize defects and store inspection results. The required user interfaces should be specified, as well as the possible triggering method for the machine vision system. Operating environment of the machine vision system should also be described, with particular emphasis on lighting conditions. Sources of ambient light or potential shadowing must be identified to support lighting optimization and illumination selection, as these are critical factors that significantly affect system performance. Furthermore, the installation space, environment

temperature, and power supply availability should be specified, as well as the presence of dust, dirt, shock, or vibration [4].

2.1.2 Field of view and working distance determination

The field of view is determined by the combination of part size, positioning variation, margin and aspect ratio of the camera, as visualized in Figure 1. The maximum part size and the maximum positioning variation define the baseline area within the part may be located. An additional margin should be included around this area, as space between the part and image edges may be required for image processing. Furthermore, the adaptation to the camera aspect ratio must also be considered [4].

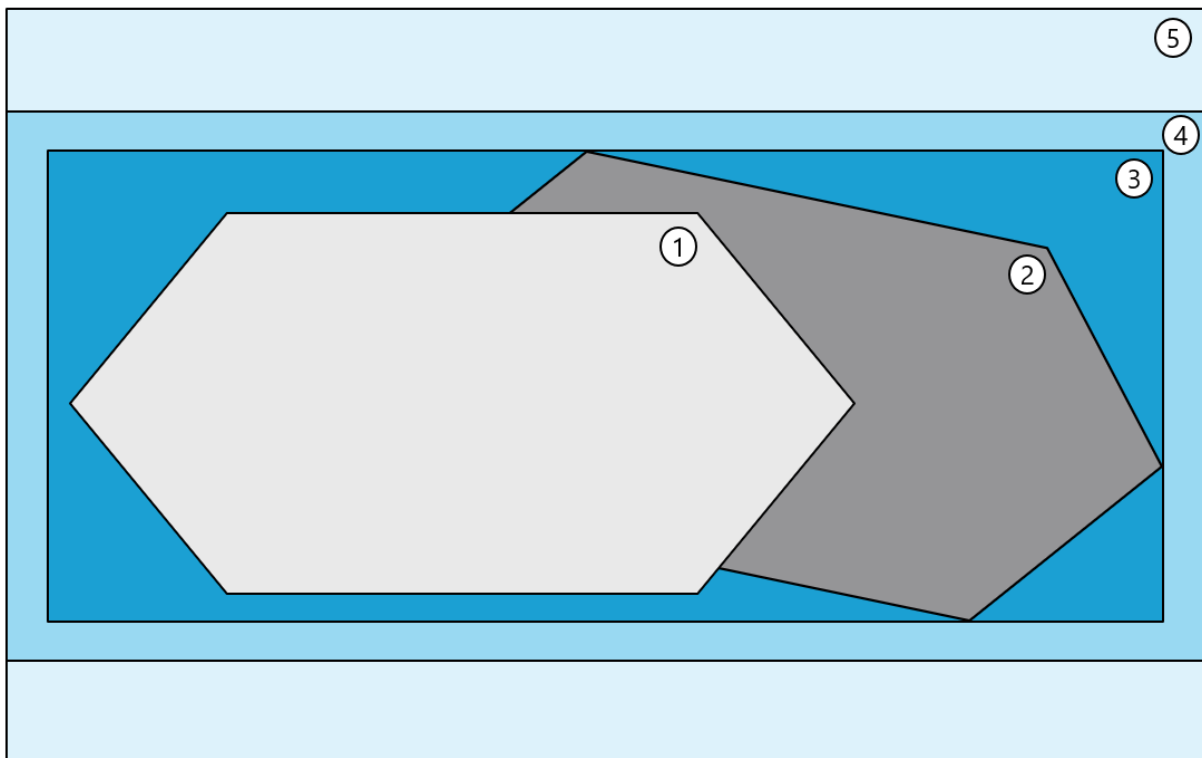


Figure 1. Visualization of field of view calculation. Object 1 represents the maximum part size, object 2 the maximum positioning variation, frame 3 the size determined by part size and positioning variation, frame 4 the additional margin, and frame 5 the adaptation of the camera aspect ratio. From: the author (2026), based on [4].

The field of view (FOV) can be calculated with the following Equation 1, where S_{part} represents the maximum part size, S_{pos} the maximum positioning variation, S_m the additional margin, and S_a the adaptation to camera aspect ratio. The field of view is calculated for both

the x and y directions, with the camera aspect ratio adaptation S_a applied only to the direction that requires scaling [4].

$$FOV = S_{part} + S_{pos} + S_m + S_a \quad (1)$$

The maximum working distance can be constrained by the physical limitations of the environment, as the space around the detectable part may be limited, and the machine vision system design should include sufficient room for the camera, lens, and illumination. The minimum working distance is constrained by the lens, as most lenses of moderate focal lengths, such as 8-25 mm, have a minimum working distance of 100 mm. The minimum working distance for lenses with higher focal lengths can be as large as 1,000 mm. There is no single working distance solution suitable for all applications, but estimates can be made based on the field of view. According to Razze, a general rule of thumb for machine vision applications is to set the working distance at a safe at least four times greater than the field of view [6].

2.1.3 Camera selection

Camera selection involves several key design considerations including resolution calculation, and the choices between monochrome or color cameras, smart or embedded cameras, and rule-based or AI-based machine vision software. Color cameras produce significantly larger datasets compared to monochrome cameras, resulting in higher computational requirements, increased system cost and longer processing times. For this reason, monochrome cameras are preferred in applications where part color is not relevant to the inspection criteria. In addition, a monochrome camera can be paired with an optical filter as a cost-effective alternative to a color camera in certain applications, such as the detection of a specific color [7].

The decision between using smart cameras, embedded vision systems or industrial cameras depends on the number of cameras required, the necessary processing power, and the overall system complexity. Smart cameras integrate the processing unit with the camera sensor, making them a simple and flexible solution for singular tasks. Embedded vision systems consists of multiple cameras connected to a shared processing unit, enabling the distribution of processing power across cameras, which is suitable for applications requiring multiple

cameras and high computational capacity. A traditional machine vision approach is using industrial cameras that transmit raw image data to an external computer for processing. These systems can also support multi-camera and high-computation applications, but their setup is more complex compared to embedded systems [4].

A crucial camera design consideration is whether to use traditional rule-based machine vision or AI-based machine vision. Rule-based machine vision relies on manually defined algorithms, such as particle analysis, edge detection, or pattern matching [7]. These are suitable for simple tasks with consistent and well-defined visual features, such as barcode reading, presence detection, or dimensional measurements. Rule-based machine vision systems are generally more cost-effective, as they typically can be implemented with minimal computational resources. Although AI-based machine vision systems can also perform such tasks, their use may be unnecessary due to higher costs. AI-based machine vision systems typically utilize convolutional neural networks, which are trained on large datasets and require high computational power, enabling them to generalize across a wide range of inputs. They are particularly well-suited for applications involving high variability and complex visual patterns, such as object classification or defect detection [2].

Camera resolution is calculated in both vertical and horizontal directions, using the field of view and system specification data. A critical aspect of resolution calculation is determining the number of pixels required to map the smallest feature, which depends on the detection algorithm and image quality. There is no universal pixel requirement to map the smallest feature that would fit all applications, but approximate values can be used based on the application. According to Rasse, detection is expected to require 3 pixels, orientation 4 pixels, recognition 10 pixels and identification 16 pixels [6]. The required camera resolution in one direction can be calculated with the following Equation 2, where R_c represents the camera resolution in pixels, FOV the field of view in millimeters, N_f the number of pixels to map the smallest feature, and S_f the size of the smallest feature in millimeters [4].

$$R_c = \frac{FOV \times N_f}{S_f} \quad (2)$$

2.1.4 Lens selection

Once the camera is selected, the supplier can provide the camera detail sheet required for lens calculation, including the camera sensor and pixel sizes. Lens selection involves several key design considerations, such as focal length calculation, lens quality evaluation, and balancing speed, depth of field, and resolution. The focal length can be calculated with the following Equation 3, where f' represents the focal length, S_s the camera sensor size, WD the working distance and FOV the field of view, with all values expressed in millimeters. The focal lengths of lenses are relatively standardized across manufacturers, meaning that the calculated focal length may not have an exact match. Since focal length and field of view are inversely proportional, the calculated focal length is typically rounded down to the nearest available option, as the field of view is usually designed close to its minimum acceptable value [6].

$$f' = \frac{S_s \times WD}{FOV} \quad (3)$$

Lens design requires balancing depth of field, diffraction-limited resolution, lighting throughput, and image acquisition speed. Increasing the f-stop number reduces the aperture size, resulting in a greater depth of field, while diffraction limited resolution, light throughput, and image acquisition speed decrease. Conversely, decreasing the f-stop number increases the aperture size, improving diffraction limited resolution, light throughput, and image acquisition speed, while reducing the depth of field. The optimal trade-off must be determined on a case-by-case basis, depending on the required depth of field, resolution, light throughput, and image acquisition speed, and should be supported by testing and consultation with the lens supplier [6].

Lens resolution can be described as spatial frequency, measured in line pairs per millimeter. The calculated spatial frequency is used together with the modulation transfer function (MTF) curve provided by the lens supplier to evaluate the required lens quality. Spatial frequency (LP/mm) can be calculated with the following Equation 4, where S_p represents the camera pixel size in millimeters [6].

$$\frac{LP}{mm} = \frac{1}{2 \times S_p} \quad (4)$$

The MTF curve represents the contrast levels achievable at different spatial frequencies and is plotted with spatial frequency on the x-axis and contrast on the y-axis, as shown in Figure 2. The calculated spatial frequency for the machine vision application will be located on the x-axis to determine whether the lens can achieve the minimum required contrast level. For machine vision applications, the minimum required contrast is typically around 20%. MTF charts usually include multiple curves representing measurements at various distances from the center of the image sensors, providing a realistic evaluation of the lens performance [6].

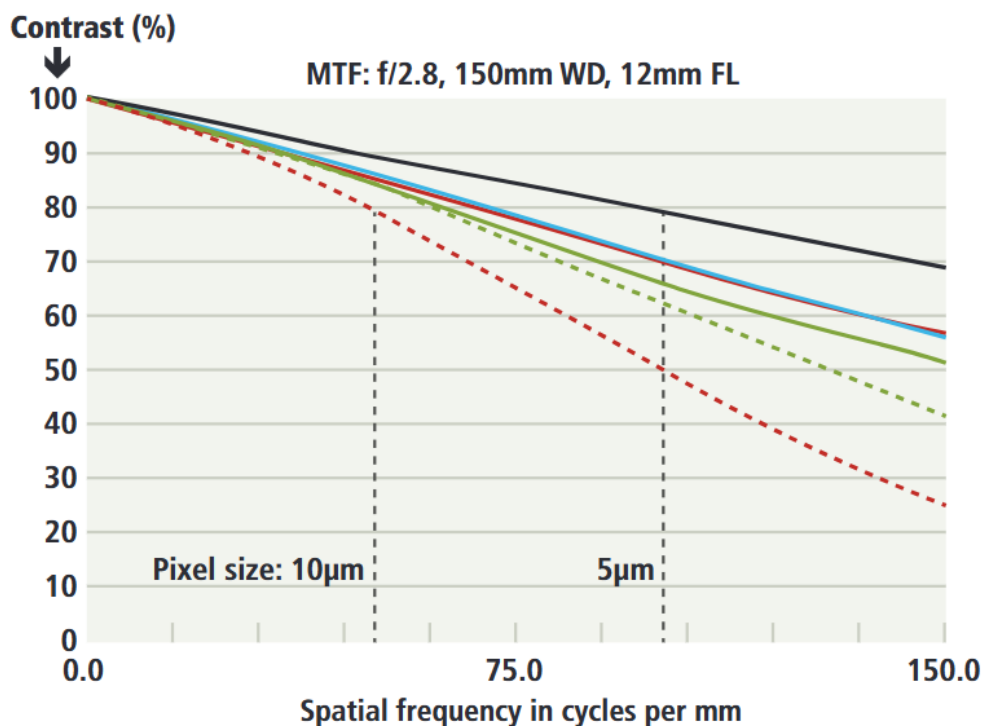


Figure 2. MTF curve of a lens, showing achievable contrast levels at different spatial frequencies and at various distances from the center of the image. From: [8].

2.1.5 Illumination selection

Optimizing illumination is one of the most critical factors in the successful design of machine vision systems, as effective illumination improves system performance and reliability while decreasing software complexity. The primary objective of illumination is to maximize the contrast features of interest while minimizing noise. The design of the illumination system includes a variety of design considerations, such as the lighting setup, light source selection and mitigation of ambient natural light. Optimizing illumination involves a combination of systematic methods, practical experience, and iterative experimentation. Therefore, applying a

theoretical framework is beneficial in guiding the process, rather than solely relying on trial and error [4].

Common lighting setup solutions in machine vision include bright field, dark field, diffused lighting, coaxial lighting, structured lighting, diffused backlighting and directional backlighting. In bright field illumination, light is directed near the camera axis, providing in contrast a brighter surface compared to other features, making it suitable for most general inspections. In dark field illumination, light is directed at a larger angle relative to the camera, providing in contrast a darker surface and brighter surface details and edges, which is effective for detecting fine surface defects. Bright field and dark field illuminations can be implemented with ring lights, bar lights, or spot lights, depending on the desired features to be illuminated [4, 9].

Diffused lighting provides illumination from multiple directions, reducing shadowing and specular reflections, and is particularly useful for inspecting glossy or curved surfaces. Coaxial lighting uses a beam splitter to direct light along the optical axis of the camera, enabling illumination in confined spaces. Structured lighting projects a predefined light grid onto the part, allowing the inspection of three-dimensional surface defects, such as dents. Diffused backlighting and directional backlighting are typically implemented using back-illuminated panels that enhance edge definition, making them suitable for shape inspection. Directional backlighting further incorporates a condenser lens to focus light towards the camera, producing high-contrast edges suitable for measurement tasks. The described illumination techniques are visualized in Figure 3 [4, 9].

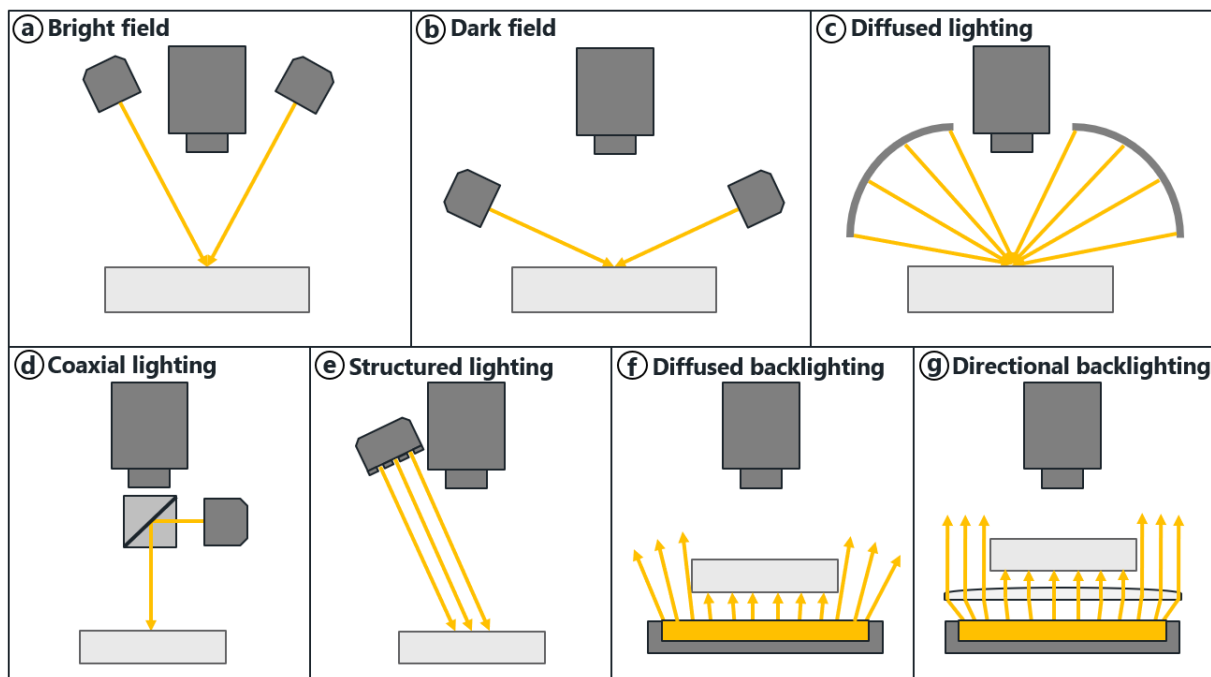


Figure 3. Typical illumination techniques used in machine vision. (a) represents bright field, (b) dark field, (c) diffused lighting, (d) coaxial lighting, (e) structured lighting, (f) diffused backlighting, and box (g) directional backlighting. From: the author (2026), based on [4, 9].

LED lights are the most commonly used light source in machine vision applications due to their long lifespan, stable light output, and precise controllability. Alternative light sources include fluorescent lamps which have a shorter lifespan and are mainly suitable for static continuous lighting, and xenon lamps which provide strong light intensity but shorter lifespan and higher costs. Despite the long lifespans of LED lights, Hornberg recommends setting the brightness of the light source to 50% to minimize aging and extend lifetime. LED lights also enable the ability to use various wavelengths, even infrared and ultraviolet. The most effective way to illuminate a colored part is often to use a corresponding light color, such as red light for red-colored parts and blue light for blue-colored parts. White light or infrared light can be advantageous when inspecting parts of varying colors, as white light provides neutral illumination and infrared light can reduce grayscale variation between colors. In some machine vision applications involving very small features, ultraviolet illumination may be required, as certain features are only visible under these wavelengths [4, 10].

Polarization can be implemented by placing a polarizing filter in front of the camera to reduce glare from shiny surfaces, or by using polarizing filters in both the light source and the camera enhance contrast of reflective features while minimizing glare. The polarizing filters work by blocking light waves that vibrate in certain directions, thereby minimizing reflections.

Additional filters used in machine vision applications include neutral density filters that reduce the overall brightness of the images, and bandpass, longpass and shortpass filters that block specific wavelengths, which can be used to emphasize color information of monochrome images. Most machine vision cameras also contain built-in wide band pass filters that block ultraviolet and infrared light to improve the image quality in the visible spectrum [4, 9].

Lighting conditions in industrial environments differ from laboratory due to ambient lighting. Ambient lighting includes both sunlight entering through windows and illumination from the factory environment. Its effects can be minimized by using sufficiently strong illumination to overcome ambient lighting. In some cases, ambient lighting can also be reduced by using enclosures or covers. Additionally, shorter exposure time, higher f-stop number, or flash lighting can help mitigate the influences of ambient lighting [4].

2.1.6 Mechanical, electrical and robotic design

Machine vision equipment mounting frames and fixtures must provide both sufficient adjustability and mechanical rigidity. Adjustability of the cameras and illumination is required for installation, operation, and maintenance, and therefore the setup should allow the required degrees of freedom to be changed independently. At the same time, mounting frames and fixtures must be designed with adequate mechanical rigidity to withstand potential environmental stresses such as vibration or shock. The power supply requirements and cabling should be specified, and cable lengths should be sufficient while maintaining acceptable bending limits. Additionally, adequate housing should be included when required due to environmental factors such as dust or dirt [4].

Some machine vision applications require images from multiple locations or angles, for which robots can be used as an alternative to multiple fixed cameras. The design of the robot station includes layout design, selection of the robot and associated equipment, and design of safety measures. The robot station design process begins with defining the task by conducting a process study and decomposing the task down to sub-tasks. This is followed by determining the task sequence and space requirement for all workstations, forming the basis for layout designs. Multiple robot station layout designs can be developed and evaluated through simulations. Simulations are conducted by importing the CAD models of the product, robots and associated equipment into simulation software, creating the cell layout, defining tasks, generating optimal robot paths, and calculating cycle times. The optimum layout design can be then selected based on the predefined criteria using the information obtained from the simulations [11, 12].

Robot selection involves several key design considerations, including the maximum speed to match the required output, maximum reach and degrees of freedom to cover the required workspace, flexibility for system modifications, required accuracy, the need for human-robot interaction, total costs, and maximum payload capacity to handle the attached equipment. Although machine vision cameras are relatively lightweight, payload requirements will increase when additional equipment, such as large illumination systems, is mounted on the robot. Industrial robots have been widely used for machine vision applications, and collaborative robots specifically can be employed in tasks within the workspace of human operators [11, 13, 14].

The safety of the robot station must be ensured in accordance with standards ISO 10218-1 [15] and ISO 10218-2 [16] for industrial robots, and also ISO/TS 15066 [17] for collaborative robots. These standards require thorough risk assessment for all robot applications, with identified risks mitigated through layout design, equipment selection, and additional safety measures. The design must ensure that there is no risk of crushing, cutting, or impact injuries to operators. Traditional industrial robots typically require physical isolation using measures such as interlocks, light curtains, or sensors. Collaborative robots can operate within the same workspace as human operators, but the standards require the implementation of at least one of the four safe human-robot collaboration methods. The four safe human-robot collaboration

methods are safety-rated monitored stop, speed and separation modelling, hand guiding, and power and force limiting. For example, speed and separation modelling can be applied in scenarios where robots and operators work simultaneously, while safety-rated monitored stop can be used when simultaneous operation is not required [11, 13, 14].

2.1.7 TCO-based machine vision system profitability calculation

Detailed TCO-based profitability calculation is effective for evaluating the profitability of machine vision solutions, as it considers both direct and indirect costs and benefits over the system's entire lifecycle. It serves as a decision-making tool for management and engineers in selecting cost-effective implementation strategies, thereby supporting long-term profitability. The TCO-based profitability calculation should include initial investment costs, operation costs, maintenance costs, downtime costs, production costs, as well the value added and remaining value. From a timeline perspective the costs and benefits of machine vision systems can be categorized into initial costs, annual costs, annual benefits and remaining value [4, 18].

As the majority of design work is completed before the equipment costs can be accurately estimated, only the final design and testing work will be included in the initial costs of TCO-based profitability calculations. Once the testing and design are finalized, the initial costs will include hardware costs of cameras, lenses, illumination, connection cables, PCs, spare parts, test materials and system-specific hardware such as interface panels, industrial robots, or lighting covers. In addition, the initial costs will include labor costs from hardware installation, PLC coding, camera software setup, final test runs, and documentation [4, 18].

Annual costs of machine vision systems include electricity costs, maintenance work, replaced equipment, and downtime due to line stoppages. In cases where product changes are expected during the system's lifecycle, modification costs should also be considered. Maintenance costs may include cleaning of optical equipment if required and replacement of aging equipment, particularly illumination units. Although system errors may not always cause line stoppages, especially when cameras are only used for quality control, the associated costs of

manual inspection and system repair should be included in the TCO-based profitability calculations [4, 18].

Annual benefits of machine vision systems may include reduced manual work, quality improvement, improved safety, or increased data for production improvement. The benefits from reduced manual work is calculated with the reduced salary costs including pension and insurance fees. Benefits from quality improvement can be calculated with the reduced rework and recall costs. Benefit from increased data for production development can be estimated in cases with clear production development applications [4, 18].

The remaining value is calculated by subtracting the cost of equipment removal with the value of remaining hardware. Removal costs can be estimated based on labor requirements while the value of remaining hardware depends on the condition of the equipment and its potential for reuse in the future. If the system can be reused for similar applications, the value of the hardware may remain relatively high. Machine vision cameras are relatively reusable, with resolution and camera software being primary limiting factors. However, application specific equipment such as lenses with fixed focal lengths may have limited reuse potential. Illumination components may be reused, although their value may be reduced due to aging [4, 18].

After determining the initial costs, annual costs, annual benefits, and remaining value, profitability measures can be calculated to support the investment decision. Common engineering economics measures include net present value (NPV), internal rate of return (IRR), profitability index (PI), and payback time (PB). These metrics provide complementary perspectives, and it is often beneficial to use multiple indicators for a comprehensive profitability evaluation. A yearly discount rate of 15% is applied to future cash flows in the net present value and profitability index calculations to reflect the high-tech investment in a rapidly evolving automotive industry [19].

Net present value is one of the most effective methods for evaluating project profitability, as it is easy to understand and takes into account all cash flows and their time value. A project is considered profitable if the net present value exceeds zero, as the calculated value provides the total net value of a project's future cash flow discounted to the present day. The net present value can be calculated with the following Equation 5, where B_t represents annual benefits, C_t annual costs, B_r remaining value, C_0 initial costs, t the year, and n the project lifetime in years [19].

$$NPV(15\%) = \sum_{t=1}^n \frac{B_t - C_t}{(1.15)^t} + \frac{B_r}{(1.15)^n} - C_0 \quad (5)$$

The internal rate of return expresses the annual return of the project, and it can be used to assess whether the returns exceed the company's required return. The internal rate of return can be calculated with following Equation 6, solving for IRR , with B_t representing the annual benefits, C_t the annual costs, B_r the remaining value, C_0 the initial costs, t the year, and n the project lifetime in years [19].

$$0 = \sum_{t=1}^n \frac{B_t - C_t}{(IRR)^t} + \frac{B_r}{(IRR)^n} - C_0 \quad (6)$$

The profitability index expresses the return of the project per investment, and a project is considered profitable if the calculated value exceeds 1.00, with higher values indicating greater profitability. The profitability index can be calculated with the following Equation 7, where B_t represents the annual benefits, C_t the annual costs, B_r the remaining value, C_0 the initial costs, t the year, and n the project lifetime in years [19].

$$PI(15\%) = \frac{\sum_{t=1}^n \frac{B_t}{(1.15)^t} + \frac{B_r}{(1.15)^n}}{C_0 + \sum_{t=1}^n \frac{C_t}{(1.15)^t}} \quad (7)$$

The payback period estimates the time required to recover the initial investment. Although it does not account for the time value of money or remaining value, it provides useful insight into project risk, particularly for short-term investments. It is most appropriate for projects with payback times measured in months instead of years, since the exclusion of remaining value and time value has less impact in such cases. The payback time in months can be calculated with the following Equation 8, where C_0 represents the initial costs, B_t the annual benefits, and C_t the annual costs [19, 20].

$$PB_m = \frac{C_0}{B_t - C_t} \times 12 \quad (8)$$

2.1.8 Implementation of machine vision systems

If the TCO-based profitability calculations demonstrate that the machine vision system is profitable and management approves the project, the implementation can begin. The implementation of a machine vision system typically begins with a project kick-off meeting, which establishes the base for a successful project. The meeting communicates the project's scope, objectives, and timeline to all stakeholders and defines their roles and responsibilities. The kick-off meeting is followed by testing, maintenance planning, procurement, installation, final test runs, personnel training, and documentation [4, 18].

The machine vision system can be tested after the initial design phase to verify feasibility. Whenever possible, testing should be conducted at the actual application site to ensure realistic conditions. If this is not possible, laboratory testing can provide preliminary insights, but it should be noted that laboratory lighting conditions may differ significantly from those on the factory floor. Hornberg suggests dividing the installation into two phases; hardware installation and software setup. Hardware installation can begin as soon as the equipment is available, allowing verification of system reliability and image quality prior to setting up the camera software. Camera software setup differs between traditional rule-based and AI-based machine vision systems. Rule-based systems require manual configuration, including techniques such as particle analysis, edge detection, and pattern matching, where detection parameters and regions of interest are explicitly defined [7]. In contrast, AI-based systems are trained using labelled datasets, enabling the model to automatically learn relevant features [2]. If issues arise during testing, the system design can be revised and retested with updated equipment [4].

Once feasibility has been confirmed, the required equipment and spare parts can be procured. Spare part requirements and maintenance planning depend on equipment lifetimes, system criticality, and the likelihood of component failure. Typically, maintenance activities for machine vision systems include replacing illumination components at the end of their lifespan, occasionally replacing faulty hardware, and in some cases cleaning the lenses due to environmental factors [21, 22]. Following procurement, the machine vision system can be

installed and the camera software set up, after which final test runs are conducted to confirm system performance. Relevant production personnel should be trained in system operation and basic troubleshooting, while maintenance personnel should be trained in system operation, troubleshooting, repair, and maintenance of the system. Once the system is verified to be fully operational, and all training and documentation are complete, the project can be concluded with a handover to production [4, 18].

2.2 Machine vision solutions in the industry

The purpose of the research on machine vision solutions is to identify advanced machine vision systems and gain insights into their feasibility and design. The research on machine vision solutions consists of researching machine vision solutions reported in literature, offered by suppliers, and implemented by other manufacturers. The identified machine vision applications include paint defect inspection and panel gap and flush inspection using machine vision tunnels and robot stations, as well as tool positioning and fastener assembly verification with machine vision.

2.2.1 Paint surface inspection

Paint surface inspection can be performed using machine vision tunnels or robot stations. These systems rely on three-dimensional surface measurement techniques, with deflectometry being particularly effective for detecting surface defects of reflective surfaces. In deflectometry, a patterned screen or structured illumination is projected onto the surface while a machine vision camera captures the reflected image. AI-based machine vision is well-suited for such applications as the models can be trained to detect and classify defects such as scratches and dents. Paint surface inspection using deflectometry is visualized in Figure 8 [23].

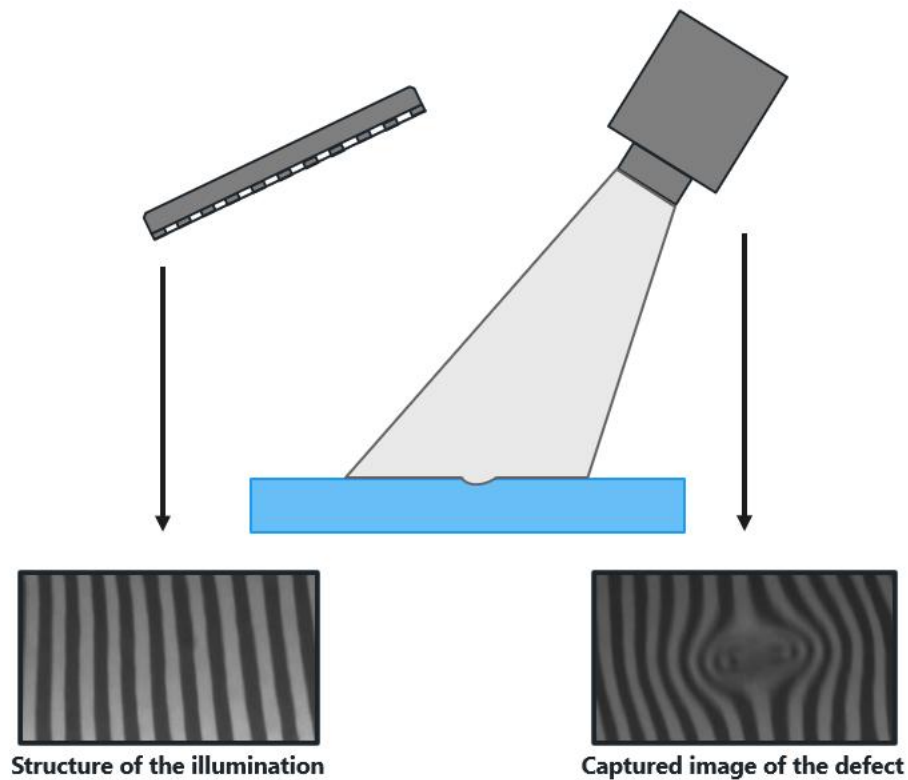


Figure 8. Surface defect inspection with a monochrome machine vision camera and structured illumination. From: the author (2026), based on [23].

Kieselbach et al. developed and tested a paint surface inspection machine vision tunnel, with the developed concept presented in Figure 9. The machine vision tunnel includes four ten-megapixel CMOS cameras for the roof, four for the bonnet, and four to six cameras for each side. With this configuration, one pixel corresponds to approximately 0.1 mm on the vehicle surface to detect defects larger than 0.2 mm. Illumination is provided by 1.9-meter LED elements with a 6000K cool-white temperature, and the tunnel is enclosed with a black illumination cover to block ambient lighting. Although the tunnel frame was designed as a rectangular structure, the authors noted that further optimization could account for the angled geometry of the roof and hood. In laboratory testing under static conditions, the system detected all defects larger than 0.2 mm on pure white test surfaces and nearly all defects on silver and deep black surfaces. However, performance in real production environments may be affected by image blur on the moving vehicles and variations in lighting conditions, even when using an illumination enclosure [24].

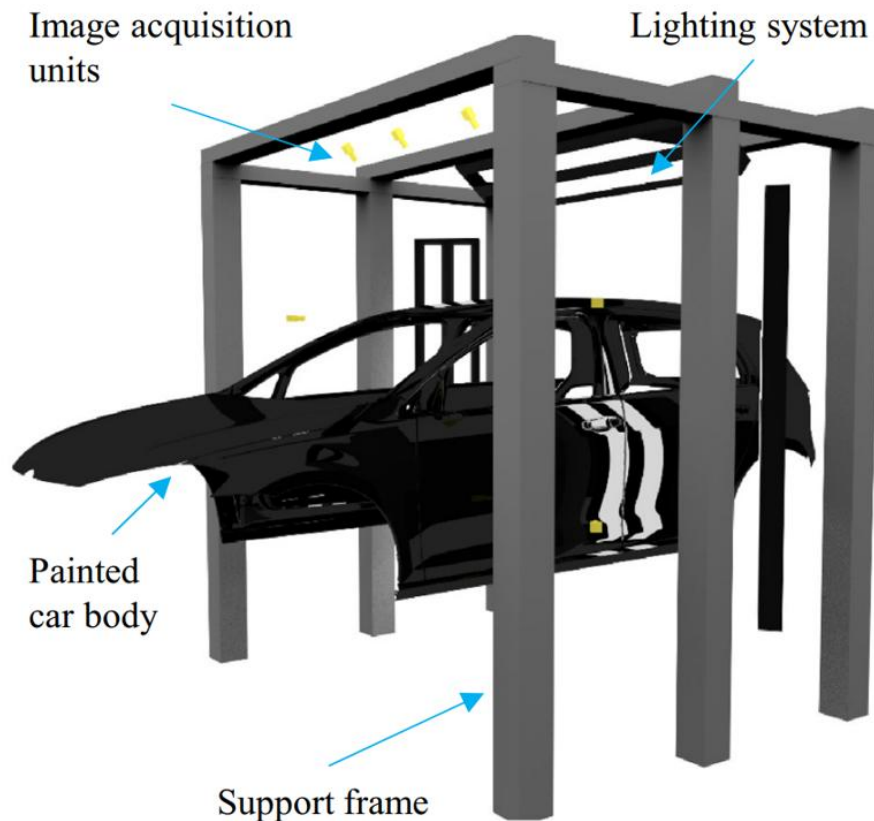


Figure 9. Machine vision paint defect inspection tunnel concept. From: Kieselbach et al. [24].

The feasibility of robotic paint defect inspection was tested in a study conducted by Akhtar et al, in which a machine vision robot station inspected the paint defects of car bumpers. The system included a KUKA industrial robotic arm, a 3.2 MP monochrome Point Grey camera with a 12.5 mm focal length Fujinon lens, a 40-inch display for structured illumination, and a separate computer for image processing. The experimental setup is presented in Figure 10. The system detected nearly all paint defects, demonstrating the feasibility of robotic inspection for such applications [25].

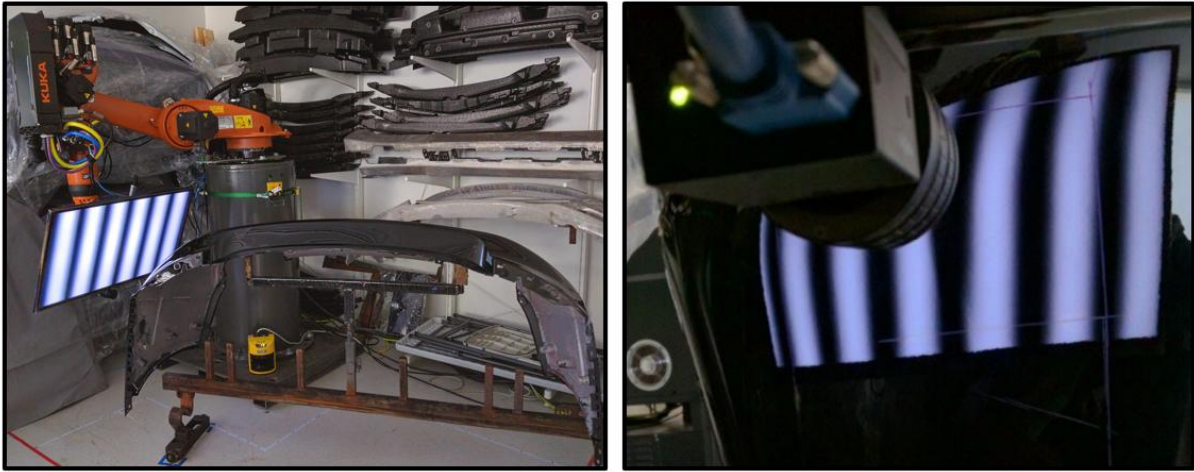


Figure 10. Robotic machine vision paint defect inspection setup. From: Akhtar et al. [25].

Machine vision paint inspection tunnels and robot stations are also available as turnkey solutions from suppliers. For example, Eines Vision has developed a paint inspection tunnel incorporating multiple cameras, continuous structured illumination, an illumination cover to block ambient light, a separate image processing unit, and a results display interface. Similarly, Isra Vision has developed robotic inspection systems consisting of industrial robots equipped with cameras and structured illumination. In both cases, the number of cameras or robots, processing requirements, and result visualization is tailored to the specific application. These supplier solutions are presented in Figure 11 [26, 27].



Figure 11. Machine vision paint inspection solutions from suppliers, with the machine vision tunnel from Eines Vision on the left and machine vision robot station from Isra Vision on the right. From: [26, 27].

2.2.2 Panel gap and flush inspection

Panel gap and flush inspection is performed to ensure aesthetic quality of vehicles in the automotive industry, and it can be automated using stereo vision or laser triangulation. The panel gap refers to the distance between adjacent panels, while flush refers to differences in relative height between panel surfaces. In the laser triangulation method, one or more laser lines are projected across the panel gap, and a machine vision camera captures the reflected laser profiles to calculate gap and flush values. In the stereo vision method, two calibrated machine vision cameras positioned at a fixed distance capture images of the panel surfaces across the gap region, enabling reconstruction of a three-dimensional representation of the panel geometry. The laser triangulation and stereo vision methods for panel gap and flush inspection are illustrated in Figure 12 [28, 29].

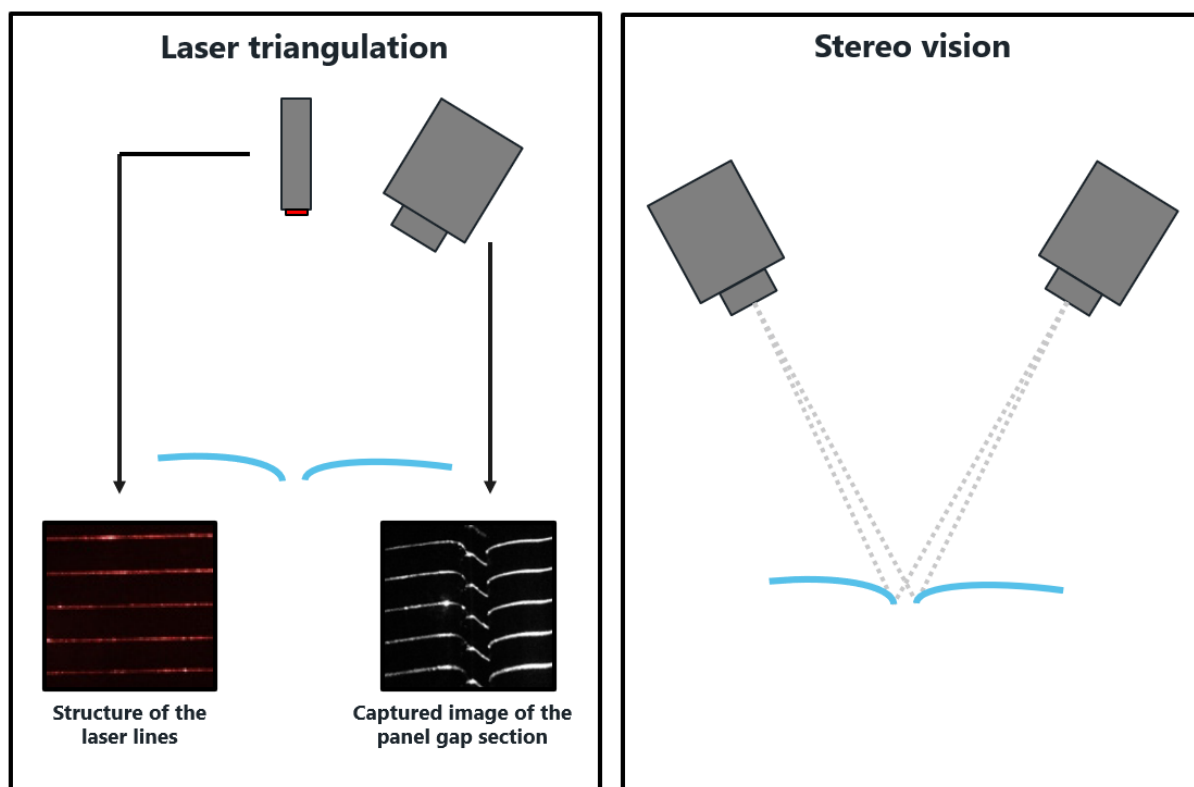


Figure 12. Panel gap and flush inspection methods, with laser triangulation method on the left and stereo vision method on the right. From: the author (2026), based on [28, 29].

Kholkhujaev et al. developed and tested a panel gap and flush inspection robot station, which is presented in Figure 13. The system includes a robotic arm, a 5-mW mono-line laser with a wavelength of 405 nm and a fan angle of 55°, a Basler Ace CMOS camera with a 2590 x 1942 resolution, an 8 mm focal length Basler lens with an aperture range of F1.8-F22 and

resolution of 5 megapixels, and a separate image processing unit. The system operates at a distance of 60-100 mm from the laser and approximately 100-150 mm from the inclined camera. The developed system achieved an accuracy of 0.01 mm for gap measurement and 0.011 mm for flush measurement, with expanded uncertainties at 0.221 mm and 0.177 mm [30].



Figure 13. Robotic panel gap and flush inspection setup. From: Kholkhujaev et al. [30].

Machine vision panel gap and flush inspection tunnels and robot stations are also available as turnkey solutions from suppliers. For example, Eines Vision has developed a stereo vision-based inspection tunnel that incorporates multiple camera pairs positioned at fixed distances, continuous bright illumination around the vehicle, an illumination cover to block ambient light, a separate processing unit, and a results display interface. Similarly, Isra Vision has developed a laser triangulation based panel gap and flush inspection robot station, which includes industrial robots equipped with a machine vision camera and a laser with a wavelength of either 405 nm or 450 nm. In both cases, the number of cameras or robots, processing requirements, and result visualization is tailored to the specific application. These supplier solutions are presented in Figure 14 [31, 32].



Figure 14. Machine vision panel gap and flush inspection solutions from suppliers, with the machine vision tunnel from Eines Vision on the left and machine vision robot station from Isra Vision on the right. From: [31, 32].

2.2.3 Tool positioning and fastener assembly verification

Fastening tools can be equipped with torque logging capabilities, but they cannot reliably associate specific torque values with individual bolts when multiple fasteners are assembled at the same station. This creates uncertainty regarding whether each bolt has been properly tightened and in the correct sequence. To address this limitation, machine vision-based tool positioning and assembly verification can be implemented to ensure that all bolts are tightened within the specific torque range and in the correct order. Several approaches exist for integrating machine vision cameras for such applications, including fixed overview cameras that monitor the entire assembly station and tool-mounted cameras that capture close-up views in confined spaces [33].

Tool-mounted cameras present a promising solution for monitoring bolt assembly in confined areas within the vehicle, where overview cameras may have limited visibility or obstructed line of sight. To experiment this approach, Rusli and Luscher conducted a study in which a camera was mounted on a fastening tool for bolt tightening inspection in the automotive assembly. The setup included an Autel MV201 video inspection camera mounted on the head of a DC fastening tool, as shown in Figure 4. The study demonstrated the feasibility of tool-mounted vision systems, but the vision system would require further improvements for industrial application. According to the authors, an industrial grade camera with at least 30 frames per second and a resolution of 640x480 would be necessary. In addition, the camera

must be compact and lightweight enough to be mounted on the tool, such as a remote head camera with a separate image processing unit [33].



Figure 4. Autel MV201 video inspection camera mounted on a fastener tool. From: Rusli and Luscher [33].

In the study, the tightening of four identical steering rack bolts in the vehicle's front subframe assembly was inspected. The distinct visual surroundings of each bolt enabled reliable identification, as illustrated in Figure 5. However, this approach may become challenging in applications where bolt surroundings are visually similar, making differentiation more difficult [33].

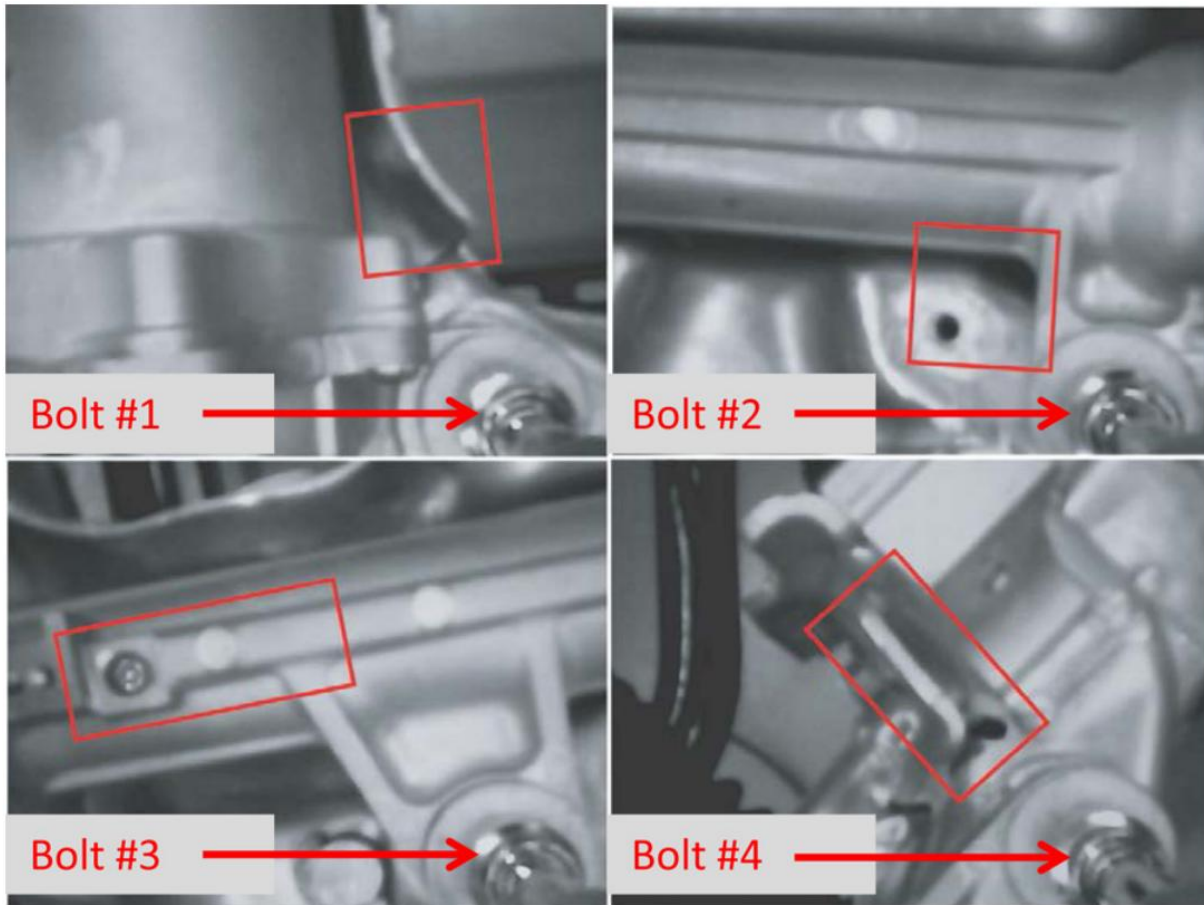


Figure 5. Video images of bolt tightening. From: Rusli and Luscher [33].

False positives in tool positioning and assembly verification are particularly critical, as they may result in torque values from one bolt being incorrectly assigned to another. This misclassification can lead to production downtime due to corrective actions and may compromise assembly integrity by allowing improperly tightened bolts to remain undetected. In contrast, false negatives are less critical, as they typically only delay the process by requiring the operator to repeat the fastening operation. Due to the severity of false positives, the recognition threshold should be set conservatively to eliminate them, even at the expense of increased false negatives. In the study by Rusli and Luscher, the assembly verification time was less than one second when the threshold was adjusted to suppress most false positives. The recognition performance for each bolt is shown in Figure 6. While threshold selection was straightforward for bolts 1, 3, and 4, bolt 2 presented challenges due to high detection scores for adjacent bolts, requiring a more conservative threshold and potentially increasing assembly time [33].

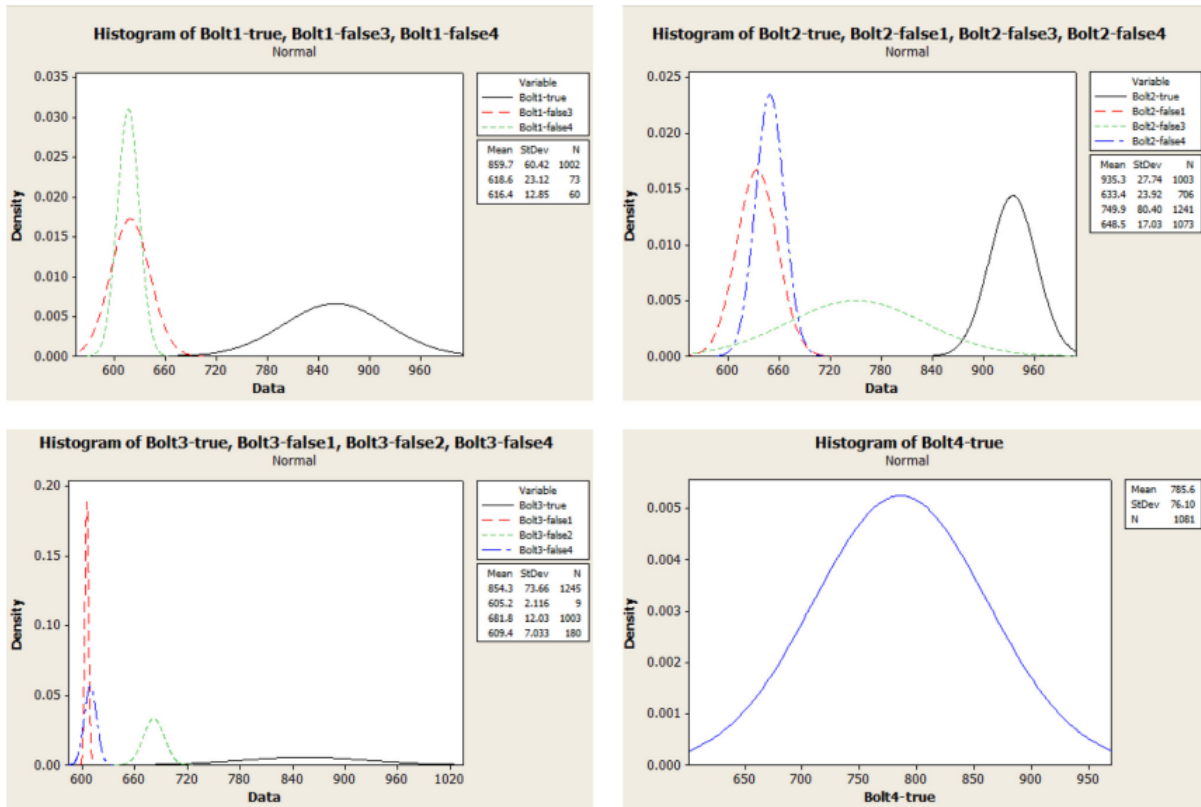


Figure 6. The system recognition data for the four different bolts, with top left presenting results for bolt 1, top right for bolt 2, bottom left for bolt 3, and bottom right for bolt 4. From: Rusli and Luscher [33].

Fastener assembly verification with tool positioning using overview cameras was tested by Turner et al. in a study conducted at a Mercedes Benz Factory in Alabama. The developed system utilized AI-based machine vision to detect the position of the fastening tool tip and the target bolt for verification of correct assembly and tightening. The system demonstrated feasibility under test conditions, but notably the testing only included easily positioned bolts on a stationary vehicle. According to the authors, the system performs reliably when bolts are spaced at least 7.5 cm apart and observed from an unobstructed camera position at a distance of approximately 2.5-3 meters. Camera images from the bolt tightening testing are presented in Figure 7 [34].

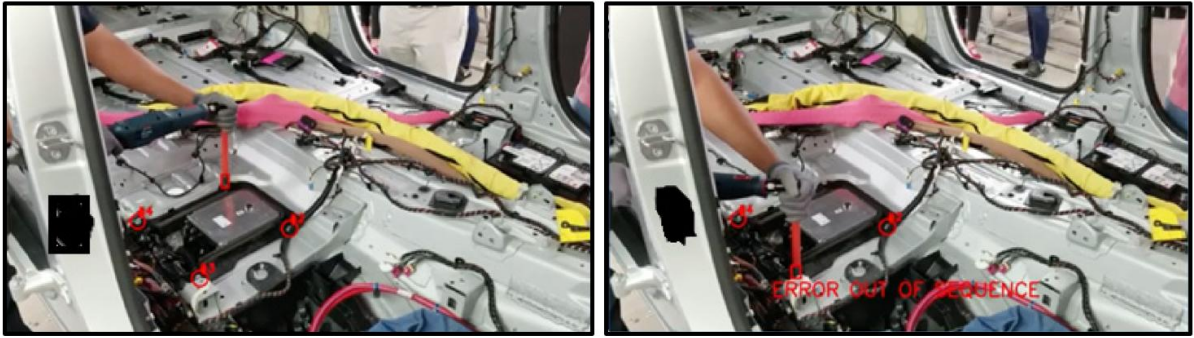


Figure 7. Camera images from bolt tightening. From: Turner et al. [34].

3 Methodology

The methodology consists of application identification through interviews and machine vision system design and profitability calculation for selected applications at Valmet Automotive.

The purpose of the interviews is to identify potential machine vision applications in Valmet Automotive's general assembly and to determine key considerations for their design and implementation. The data collected from the interviews is used to guide the methodology of machine vision application evaluation with potential machine vision applications, challenges regarding implementation and factors that should be considered in the design and implementation. The selection of machine vision applications for Valmet Automotive's general assembly is based on identifying the applications that with the highest profitability, the easiest implementation and the lowest risk of project failure.

System designs and profitability calculations are carried out for the selected machine vision applications utilizing the developed literature-based system specification list found in Appendix 1, machine vision system design list in Appendix 2, and TCO-based machine vision system profitability calculation list found in Appendix 3. The objective of the system design and TCO-based profitability calculations is to identify the processes in Valmet Automotive's general assembly that would benefit the most from machine vision implementation and to evaluate the technical and economic feasibility of the proposed systems. The opportunity for machine vision implementation depends on future manufacturing contract agreements, while the system designs are based on estimated specifications of new vehicle models and reference data from previous models. Once detailed specifications of new vehicle models become available, the machine vision system designs and TCO-based profitability calculations can be updated accordingly. If the updated calculations demonstrate profitability and management approves the projects, the proposed machine vision systems can be implemented.

3.1 Application identification through interviews

The participants for the expert interviews were selected to include relevant personnel from all key departments in the design and implementation of machine vision systems in Valmet Automotive's general assembly. In total, 14 personnel were interviewed: a lead project engineer from the advanced engineering department; senior project engineer from the general

assembly manufacturing engineering department; four process planners from the general assembly process planning department; quality engineer and two senior quality engineers from the general assembly quality department; manager, senior automation engineer and senior maintenance engineer from the general assembly maintenance department; two process operators from the general assembly production department.

Semi-structured interviews were conducted to ensure consistency across participants while allowing flexibility for in-depth discussion. The interviews questions were as follows: What potential applications do you identify for machine vision in Valmet Automotive's general assembly, what challenges do you foresee in the implementation of machine vision systems, what aspects should be considered in the implementation of machine vision systems from your department's perspective. Most interviews were conducted individually in person, but due to scheduling constraints, the interview with quality department was held as an in person small group interview and the interview with maintenance department was held remotely also as a small group interview. As there was a mix of individual and small group interviews, and the findings are based on expert opinions from a limited number of participants, the results are intended to provide qualitative insights rather than statistically generalizable conclusions. The interviews were conducted prior to the machine vision system design and TCO-based profitability calculation, as the findings were used to guide the selection of applications and the identification of key design considerations. The full interview results are presented in the results chapter.

3.2 Tire distribution system design

In addition to the applications identified through the interviews, one machine vision application at Valmet Automotive was identified prior to the interview phase. This application involves tire distribution on the tire conveyor using machine vision cameras to ensure feasibility of the conveyor in the future. In Valmet Automotive's previous tire distribution setup, tires could be sorted using a photoelectric sensor due to differing tire sizes between car models. However, in a future scenario where the conveyor includes tires of the same size for different car models, an alternative system would be required for sorting the tires. TCO-based profitability calculations were not conducted for this application, as the implementation of the

system would be necessary under such conditions. The tire separation point, where the tires are sorted after being placed on the same conveyor, is presented in Figure 15.



Figure 15. The tire separation point on the tire conveyor, where the machine vision system could be implemented. Box 1 represents the location where tires stop before being separated to their respective conveyors, and circle 2 indicates the axis along which system specification data is defined. From: the author (2026)

The tire distribution system specification list is presented in Table 1, with the data gathered through inline measurements and estimations. The minimum and maximum wheel and tire sizes were estimated to range from 205/55R16 to 235/35R19, with multiple wheel color options such as black and silver. The size of the smallest feature to be detected is depends on the distinguishable visual characteristics of the future car models, but it was estimated to be

approximately 7 mm, based on spoke geometry differences. With manual stationary positioning, the estimated tolerance along the y-axis is ± 100 mm, and the tolerance along the x-axis is estimated to be approximately 30 mm due to differing tire heights. The tolerance along the z-axis is influenced by varying tire widths and was estimated to be 30 mm. The inspection area is subject to ambient lighting, particularly from the factory ceiling windows, as well as from the fluorescent illumination from the factory. The available installation space was measured to be approximately 0.85 m along the x-axis, 1.26 m along the y-axis, and 1.76 m along the z-axis.

Table 1. Tire distribution system specification list

Tire distribution system specification list	
Description of the task	Sorting tires for different car models at the separation point on the tire conveyor
Description of the expected benefit	Ensuring the viability of the tire conveyor in cases with identical tire sizes
Size of the smallest feature to be detected	~7 mm based on spoke geometry differences
Time from inspection to result	Instant (no buffer)
Description of the part	Car wheels with tires
Part dimensions, height (min, max)	406 mm – 483 mm
Part dimensions, width (min, max)	406 mm – 483 mm
Part dimensions, depth (min, max)	205 mm - 235 mm
Color possibilities	Multiple (black, silver, etc.)
Surface finish	Glossy or matte
Corrosion, adhesives, labels, oil films, fingerprints, etc.	No
Number of different part types	Multiple
Difference between part types	Shape, size, color, surface finish
Positioning (Indexed / Manual, Continuous / Stationary)	Manual, stationary
Stationary time / speed	Confidential
Tolerance in positioning, x	~30 mm due to variation in tire height (205mm \times 0.55 – 235mm \times 0.35)
Tolerance in positioning, y	± 100 mm
Tolerance in positioning, z	30 mm due to variation in tire width
Information to be passed by interfaces	Car model identification via PLC
Installation space (x, y, z)	x = 0.85 m, y = 1.26 m, z = 1.76 m
Ambient lighting	Sun light from the factory ceiling windows and fluorescent factory illumination which could be removed or replaced with LED lights if required
Dirt / Dust	No

Tire distribution system specification list	
Shock / Vibration	No
Variations in temperature	Min 15 °C, max 35 °C, likely between 20-30 °C
Control cabinet and power supply availability	Control cabinet located approximately 2m from the tire separation point

Supplier-specific machine vision system designs were developed for four major machine vision suppliers. Each supplier was contacted with the designs regarding system cost and feasibility, and the final equipment selection was determined by cost efficiency. The following tire distribution system design is based on the selected machine vision supplier, and due to confidentiality agreements, the supplier and exact models are not disclosed.

The machine vision system will receive a trigger signal from the PLC to capture an image of the wheel once it is stationary. The system will then process the image and send identification data back to the PLC to enable correct tire distribution to the appropriate conveyors. The required field of view was calculated as 519 mm × 683 mm based on the maximum part size, positioning variation and adaptation to the camera aspect ratio, with no additional margin required. The working distance was defined to range between 1,455 mm and 1,485 mm, with the machine vision camera mounted on a box-shaped camera fixture attached to the overhead beams above the tire separation point. The camera fixture frame will be manufactured from welded steel angle irons, with the camera mounted on the roof plate. The structure is designed to minimize the vibration effects from the conveyor and to provide a stable environment for the camera. The fixture also functions as an illumination cover, with thin steel plates forming sidewalls and a roof to block ambient light from ceiling windows and factory lighting. The front plate will be bolted on to allow maintenance access, while the remaining plates will be welded. Additionally, the entire structure will be painted matte black to minimize reflections. CAD model images of the camera fixture frame are presented in Figure 16.

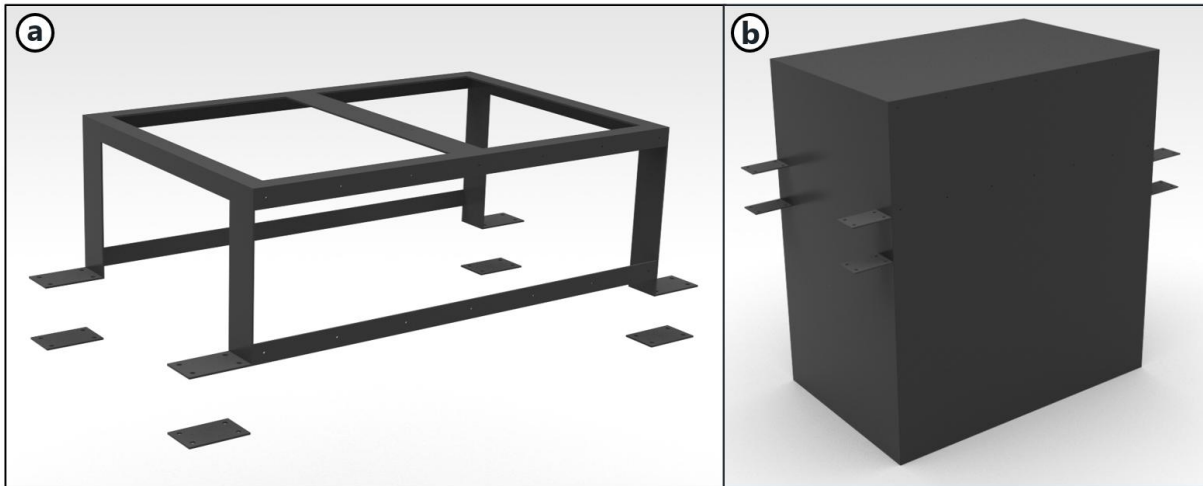


Figure 16. CAD model of the camera fixture frame for the tire distribution system, with (a) representing the frame without the illumination cover panels, and (b) with the illumination cover panels on. From: the author (2026).

AI-based machine vision is used to classify the tires based on the differing wheel spoke geometry. The minimum camera resolution was calculated as 1,186 pixels \times 1,561 pixels based on the field of view, 16 pixels to map the smallest feature in a recognition task and 7 mm size of the smallest feature. A 2 MP AI-based machine vision smart camera was selected from the supplier, as it provides sufficient resolution for the application. The lens focal length was calculated as 11.8 mm, and rounded up to an available 12 mm lens from the supplier. Rounding up the calculated focal length may cause a few millimeter clipping in images, but it is not expected to affect system functionality, as the wheel edges are not critical for classification. The supplier's camera package includes a compatible lens, meaning that the calculated lens resolution of 145 LP/mm was not required as the lens resolution should be able to match the camera. The camera includes integrated white LED illumination, which was selected as the only light source, as it is expected to provide sufficient illumination across varying wheel colors. The design decisions and calculations of the machine vision tire distribution system for the selected supplier are presented in Table 2.

Table 2. Tire distribution system design list for the selected supplier to the task

Tire distribution system design list	
Field of view calculation, $FOV = S_{part} + S_{pos} + S_m + S_a$	$FOV_x = 483 \text{ mm} + 36 \text{ mm} = 519 \text{ mm}$ $FOV_y = 483 \text{ mm} + 200 \text{ mm} = 683 \text{ mm}$
Working distance determination	$WD_{min} = 1,760 \text{ mm} - 235 \text{ mm} - 70 \text{ mm}$ $= 1,455 \text{ mm}$

Tire distribution system design list	
	$WD_{max} = 1,760 \text{ mm} - 205 \text{ mm} - 70 \text{ mm}$ $= 1,485 \text{ mm}$
Monochrome camera / Color camera	Monochrome
Smart cameras / Embedded vision system / Industrial cameras	A single smart camera
System software (Traditional rule-based machine vision / AI-based machine vision)	AI-based machine vision
Camera resolution calculation, $R_c = \frac{FOV \times N_f}{S_f}$	$R_{c,x} = \frac{519 \text{ mm} \times 16 \text{ pixels}}{7 \text{ mm}} \approx 1,186 \text{ pixels}$ $R_{c,y} = \frac{683 \text{ mm} \times 16 \text{ pixels}}{7 \text{ mm}} \approx 1,561 \text{ pixels}$
Selected camera:	A 2 MP smart camera with AI-based machine vision software
Focal length calculation $f' = \frac{S_s \times WD}{FOV}$	$f'_x = \frac{1,216 \times 3.45 \times 10^{-3} \text{ mm} \times 1,455 \text{ mm}}{519 \text{ mm}}$ $\approx 11.8 \text{ mm}$ $f'_y = \frac{1,600 \times 3.45 \times 10^{-3} \text{ mm} \times 1,455 \text{ mm}}{683 \text{ mm}}$ $\approx 11.8 \text{ mm}$
Lens resolution calculation $\frac{LP}{\text{mm}} = \frac{1}{2 \times S_p}$	$\frac{LP}{\text{mm}} = \frac{1}{2 \times 3.45 \times 10^{-3} \text{ mm}} \approx 145 \frac{LP}{\text{mm}}$
Selected lens:	A 12 mm focal length lens
Illumination technique (Bright field / Dark field / Diffused lighting / Coaxial lighting / Structured lighting / Diffused backlighting / Directional backlighting)	Bright field
Illumination type (Ring light / Bar lights / Spot light / Structured light / Panel)	Integrated camera lights
Illumination lighting type (LED / Fluorescent / Xenon)	LED
Illumination color (White / Colored / Infrared / Ultraviolet)	White
Selected illumination:	Integrated white LED camera lights
Mounting frame design	Camera fixture frame attached to the overhead beams and manufactured from welded steel angle irons
Equipment fixture design	Camera bolted to the camera fixture frame
System control and power supply design	Approximately 5m of camera cables
System specific equipment design (Illumination cover / Robotics)	Illumination cover as matte black painted steel panels attached to the camera fixture frame with a removable front panel for maintenance

3.3 Plug installation inspection design and profitability calculation

One of the machine vision applications identified through interviews is the inspection of plug installation on the vehicle underbody. Currently, Valmet Automotive's quality control relies on manual inspection by personnel to verify the correct assembly of components, such as underbody plugs. Missing plugs are either detected on the quality control area or later in the assembly process. When missing plugs are identified after the quality control area, excessive rework is required to correct the issue. Implementing a machine vision system to verify plug installation presents a viable solution to reduce rework while also freeing quality inspectors to focus on other critical inspection tasks. The quality control area at the start of assembly line 2, where the machine vision system for plug inspection could be implemented, is presented in Figure 18.

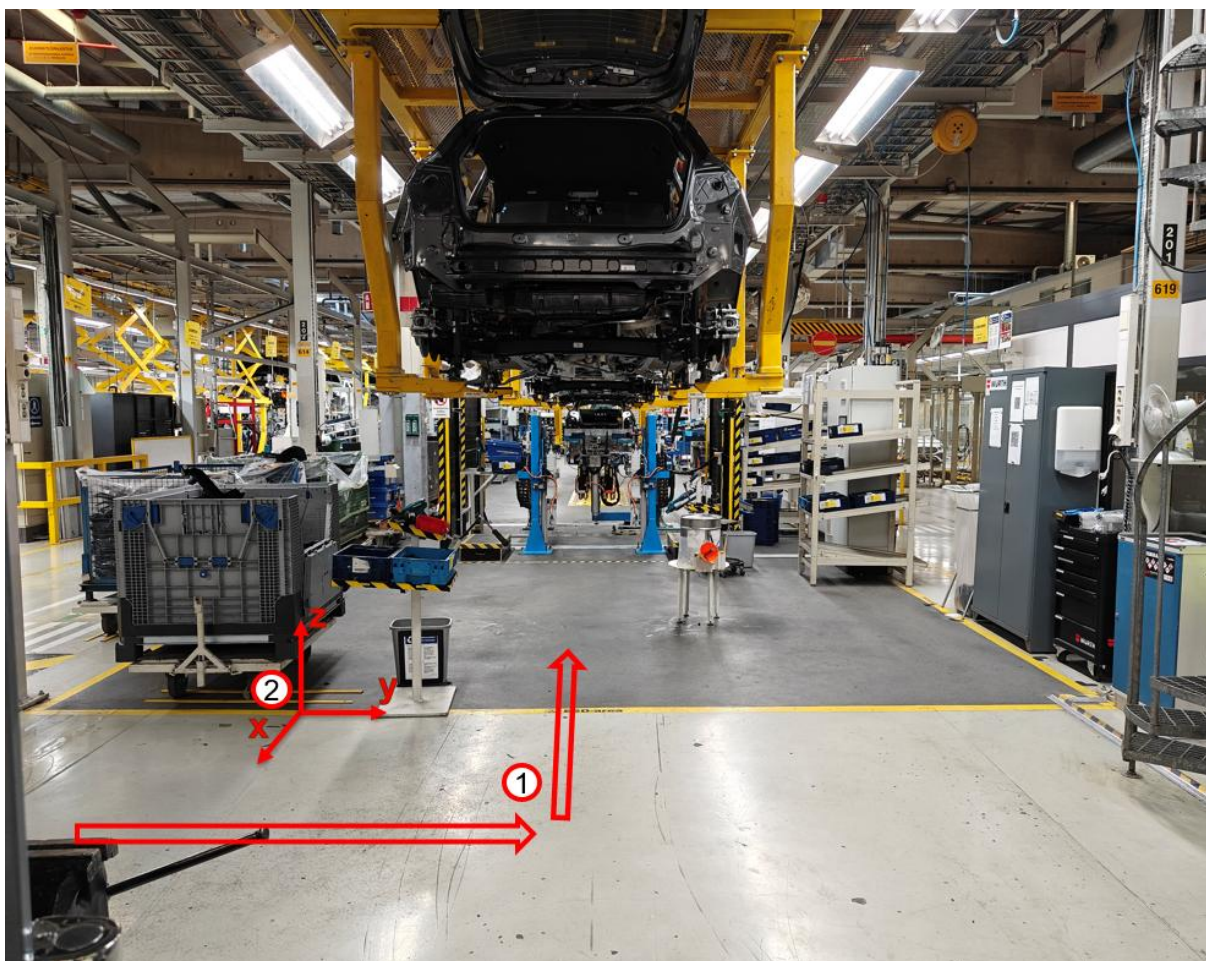


Figure 18. Quality control area at the start of assembly line 2, where the plug installation inspection machine vision system could be implemented. Circle 1 arrows indicate the direction of vehicle movement on the conveyor, and circle 2 indicates the axis along which system specification data is defined. From: the author (2026).

The plug inspection system specification list is presented in Table 3, with the data gathered through inline measurements, CAD models, and estimations. The inspectable plugs are matte black and vary in shape, while the surrounding surfaces vary on the exterior paint color of the vehicle. The upcoming car models are expected to be approximately the size of medium-sized hatchbacks with a previously manufactured model used as a reference for the design. The underbody width of the upcoming car models is estimated to be approximately 1,600 mm, and the plug dimensions are expected to range from a radius of 5 mm to 20 mm. With indexed positioning, the estimated tolerances are ± 15 mm along the x-axis, ± 25 mm along the y-axis, and ± 20 mm along the z-axis. The inspection area is subject to ambient lighting from both factory fluorescent lighting and ceiling windows. The available installation space is approximately 5 m along the x-axis, 8 m along the y-axis, and 1.8 m along the z-axis, with the vehicle underbody located at a height of approximately 2.1 m from the ground.

Table 3. Plug installation inspection specification list

Plug installation inspection specification list	
Description of the task	Verification of plug installation on the vehicle underbody
Description of the expected benefit	Missing plugs may allow water ingress into areas designed to be watertight. Automated verification is expected to prevent such defects and reduce rework.
Size of the smallest feature to be detected	10 mm
Time from inspection to result	Instant (no buffer)
Description of the part	Black rubber plugs on the vehicle underbody
Part dimensions, height (min, max)	10 mm – 40 mm
Part dimensions, width (min, max)	10 mm – 40 mm for the plug width. approximately 1,600 mm for the underbody width and 400 mm for the wheel housings widths.
Part dimensions, depth (min, max)	1 mm – 5 mm
Color possibilities	Black
Surface finish	Matte
Corrosion, adhesives, labels, oil films, fingerprints, etc.	No
Number of different part types	Multiple
Difference between part types	Different plugs shapes and locations
Positioning (Indexed / Manual, Continuous / Stationary)	Indexed, and stationary or continuous depending on camera placement
Stationary time / speed	Confidential
Tolerance in positioning, x	± 15 mm

Plug installation inspection specification list	
Tolerance in positioning, y	±25 mm
Tolerance in positioning, z	±20 mm
Information to be passed by interfaces	OK / NOK result, with defect locations presented on an HMI panel
Installation space (x, y, z)	x = 5 m, y = 8 m, z = 1,8 m. Car underbody at a height of 2.1 m from the ground
Ambient lighting	Sun light from the factory ceiling windows and fluorescent factory illumination which could be removed or replaced with LED lights if required
Dirt / Dust	No
Shock / Vibration	No
Variations in temperature	Min 15 °C, max 35 °C, likely between 20-30 °C
Control cabinet and power supply availability	A control cabinet ~10m away from the plug inspection point on the other side of the quality control area

Supplier-specific machine vision system designs were developed for four major machine vision suppliers. Each supplier was contacted with the designs regarding system cost and feasibility, and the final equipment selection was determined by cost efficiency. The following plug installation inspection system design is based on the selected machine vision supplier, and due to confidentiality agreements, the supplier and exact models are not disclosed. The system will receive a trigger signal from the PLC to start capturing images of the vehicle underbody during transfer to the quality inspection area. The system will then process the image and send presence data back to the PLC, with defect locations shown on an HMI panel. By capturing multiple images of the car during transfer, the cameras can cover the entire underbody without the need for robotics or an excessive number of cameras. The underbody plugs can be detected using a single camera, as they are oriented downwards. However, some plugs on the wheel housings face outwards, meaning separate angled cameras are required for the left and right sides. The wheel housing cameras are angled 20° backwards and 45° inwards for a full coverage of the wheel housing plugs.

The field of view was calculated as 1,650 mm × 1,100 mm for the underbody and 460 mm × 353 mm for both wheel housings, with the calculations based on maximum part sizes, positioning variations, additional margins, and adaptations to camera aspect ratios. The cameras are mounted on camera fixture frames providing working distance of 1,950 mm for

the underbody camera and 1,350 mm for the angled wheel housing cameras. The camera fixture frames will be bolted to the ground and manufactured from welded steel angle irons and steel plates, with the cameras mounted on top. The wheel housing cameras additionally include adjustable angle mechanisms, enabling modular adaptation to product changes and allowing precise system setup. The CAD models of the camera fixture frames are presented in Figure 19.

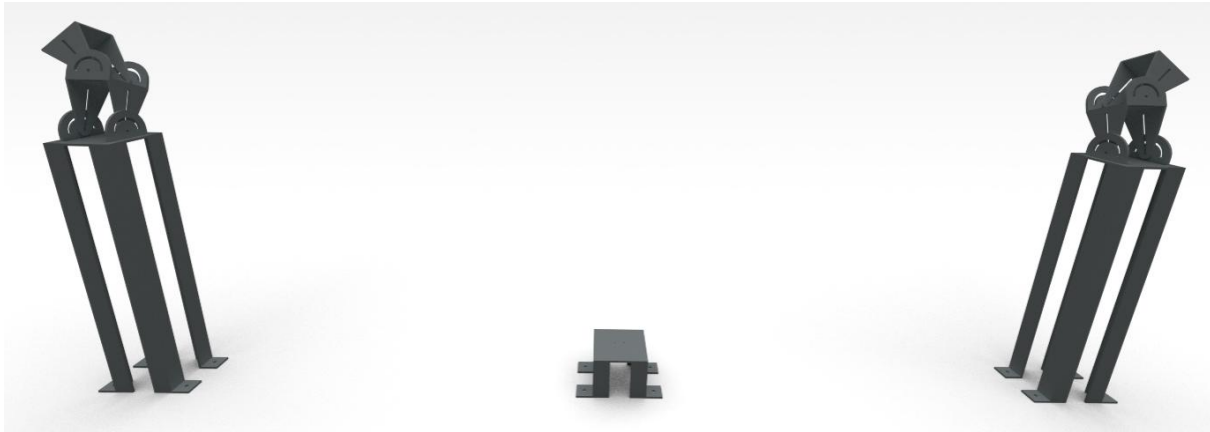


Figure 19. The camera fixture CAD models for the plug installation inspection system. From: the author (2026)

Monochrome smart cameras are used, as color identification would be unnecessary for the task, and the low camera count does not justify an embedded vision system. Additionally, the presence verification will be handled with traditional rule-based camera software. The minimum camera resolution was calculated as $1,860 \text{ pixels} \times 1,100 \text{ pixels}$ for the underbody camera based on field of view, 10 pixels to map the smallest feature and 10 mm size of the smallest feature. Presence verification can typically be handled with fewer pixels per feature, but 10 pixels were selected to account for ambient lighting and fluorescent illumination potentially reducing feature contrast. The minimum camera resolution for the wheel housing cameras was calculated as $657 \text{ pixels} \times 504$ based on field of view, 10 pixels to map the smallest feature and 7 mm size of the smallest feature. The size of the smallest feature was reduced for the wheel housing camera calculations, as plugs will appear smaller in the images due to being slightly angled. One 2.4 MP and two 0.4 MP rule-based machine vision cameras were selected from the supplier, as they provide sufficient resolution for the application.

The lens focal length for the underbody camera was calculated as 5.1 mm, which was rounded down to an available 5 mm lens from the supplier, and 15.8 mm for the wheel housing cameras, which was rounded down to available 15 mm lenses from the supplier.

The supplier's camera packages includes compatible lenses, meaning that the calculated lens resolutions of 227 LP/mm for the underbody camera and 72 LP/mm for the underbody cameras were not required as the lens resolutions should be able to match the cameras. The cameras by default include white LED lights attached to the camera, but these were replaced for infrared lights as they should sufficiently illuminate both the rubber plugs and varying vehicle paint colors. Additionally, nearby fluorescent factory illumination can be replaced with LED tubes if required to prevent interference with imaging. The calculations and design decisions of the machine vision plug installation inspection system for the selected supplier are presented in Table 4.

Table 4. Plug installation inspection design list for the selected supplier

Plug installation inspection design list	
Field of view calculation, $FOV = S_{part} + S_{pos} + S_m + S_a$	$FOV_{Underbody,X} = 1,600 \text{ mm} + 50 \text{ mm}$ $= 1,650 \text{ mm}$ $FOV_{Underbody,Y} = 40 \text{ mm} + 30 \text{ mm} + 10 \text{ mm}$ $+ 1,020 \text{ mm} = 1,100 \text{ mm}$ $FOV_{Housing,X} = 400 \text{ mm} + 50 \text{ mm} + 10 \text{ mm}$ $= 460 \text{ mm}$ $FOV_{Housing,Y} = 40 \text{ mm} + 30 \text{ mm} + 10 \text{ mm}$ $+ 273 \text{ mm} = 353 \text{ mm}$
Working distance determination	$WD_{Underbody} = 1,950 \text{ mm}$ $WD_{Housing} = 1,350 \text{ mm}$
Monochrome camera / Color camera	Monochrome
Smart cameras / Embedded vision system / Industrial cameras	Three smart cameras; cameras for left and right wheel housings angled 20° degrees backwards and 45° degrees inwards, and one camera for the underbody
System software (Traditional rule-based machine vision / AI-based machine vision)	Traditional rule-based machine vision
Camera resolution calculation, $R_c = \frac{FOV \times N_f}{S_f}$	$R_{Underbody,X} = \frac{1,860 \text{ mm} \times 10 \text{ pixels}}{10 \text{ mm}}$ $= 1,860 \text{ pixels}$ $R_{Underbody,Y} = \frac{1,100 \text{ mm} \times 10 \text{ pixels}}{10 \text{ mm}}$ $= 1,100 \text{ pixels}$ $R_{Housing,X} = \frac{460 \text{ mm} \times 10 \text{ pixels}}{7 \text{ mm}} \approx 657 \text{ pixels}$

Plug installation inspection design list	
	$R_{Housing,Y} = \frac{353 \text{ mm} \times 10 \text{ pixels}}{7 \text{ mm}} \approx 504 \text{ pixels}$
Selected cameras:	Underbody: one 2.4 MP smart camera with rule-based machine vision software Wheel housings: two 0.4 MP smart cameras with rule-based machine vision software
Focal length calculation $f' = \frac{S_s \times WD}{FOV}$	$f'_{Underbody,X} = \frac{1,920 \times 2.2 \times 10^{-3} \text{ mm} \times 1,950 \text{ mm}}{1,650 \text{ mm}} \approx 5 \text{ mm}$ $f'_{Underbody,Y} = \frac{1,280 \times 2.2 \times 10^{-3} \text{ mm} \times 1,950 \text{ mm}}{1,110 \text{ mm}} \approx 5 \text{ mm}$ $f'_{Housing,X} = \frac{704 \times 6.9 \times 10^{-3} \text{ mm} \times 1,350 \text{ mm}}{460 \text{ mm}} \approx 15 \text{ mm}$ $f'_{Housing,Y} = \frac{540 \times 6.9 \times 10^{-3} \text{ mm} \times 1,350 \text{ mm}}{353 \text{ mm}} \approx 15 \text{ mm}$
Lens resolution calculation $\frac{LP}{mm} = \frac{10000}{2 \times S_p}$	$\frac{LP}{mm} (Underbody) = \frac{1}{2 \times 2.2 \times 10^{-3} \text{ mm}} \approx 227 \frac{LP}{mm}$ $\frac{LP}{mm} (Housing) = \frac{1}{2 \times 2.2 \times 10^{-3} \text{ mm}} \approx 72 \frac{LP}{mm}$
Selected lenses:	Underbody: one 5 mm focal length lens Wheel housings: two 15 mm focal length lenses
Illumination technique (Bright field / Dark field / Diffused lighting / Coaxial lighting / Structured lighting / diffused backlighting / Directional backlighting)	Bright field
Illumination type (Ring light / Bar lights / Spot light / Structured light / Panel)	Integrated camera lights
Illumination lighting type (LED / Fluorescent / Xenon)	LED
Illumination color (White / Colored / Infrared / Ultraviolet)	Infrared
Selected illumination:	Integrated infrared LED camera lights
Mounting frame design	Floor-mounted camera fixture frames manufactured from welded steel angle irons, with the cameras mounted on the top
Equipment fixture design	Cameras bolted to the steel structure
System control and power supply design	Approximately 30m of camera cables required with the cables going above the quality control area
System specific equipment design (Illumination cover / Robotics)	Nearby fluorescent factory illumination can be replaced with LED tubes if required to prevent them interference with imaging

The profitability calculations were completed for the developed plug installation inspection system using the TCO-based profitability calculation sheet by listing the initial costs, annual costs, annual benefits and remaining value, and calculating the net present value, internal rate of return, profitability index and payback time. A yearly discount rate of 15% was applied for future cash flows in the net present value and profitability index calculations to reflect the technical complexity and associated risk of machine vision investments in the quickly transforming automotive industry. Equipment costs were provided by the supplier and the implementation costs were estimated based on system complexity and previous machine vision projects. Annual benefits were estimated based on reduced rework due to missing plugs after the quality control area, as well as reduced inspection time within the quality control process. With the future production volume to be refined later, a reference value of 30,000 cars manufactured per year for the next five years was used in the calculations. The remaining value of the hardware after five years was conservatively set to 0 €, as although the system could likely be reused in future production lines, future manufacturing specifications are not yet defined. The TCO-based profitability calculation results of the plug installation inspection system are presented in the results chapter.

3.4 Paint surface inspection design and profitability calculation

Another machine vision application identified through interviews is paint surface inspection. Currently, Valmet Automotive's paint surface inspection relies on manual inspection to detect scratches and dents at the end of general assembly, before shipment to customers. The implementation of machine vision-based paint surface inspection presents a viable option to replace this manual process. Feasible machine vision system concepts for the paint inspection include a machine vision tunnel or a machine vision robot station, which could be either in-house developed or acquired as a turnkey solution from an external supplier. The paint inspection in Valmet Automotive's general assembly, located after the water testing and before the vehicle shipment, is shown in Figure 20.

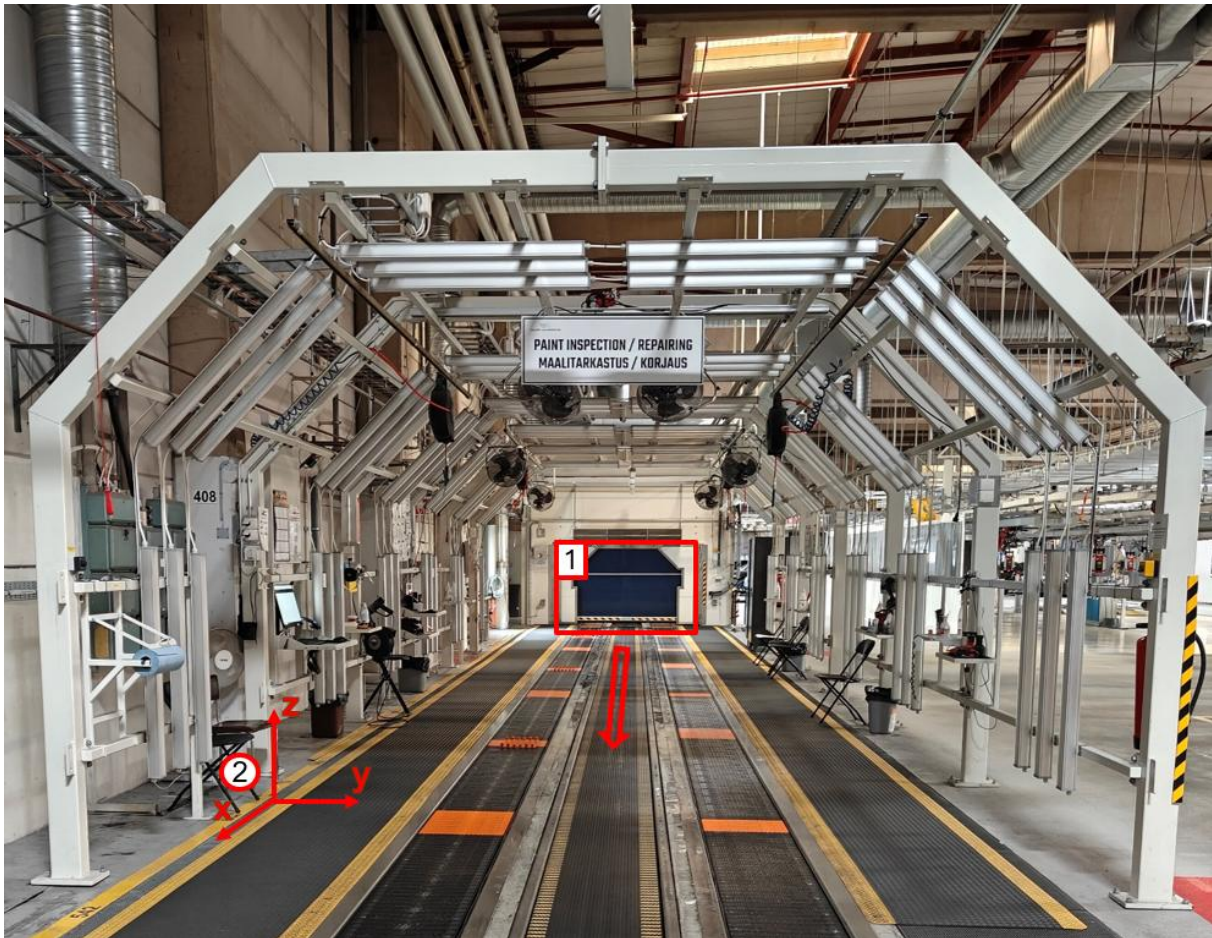


Figure 20. The current manual paint inspection location, where the paint inspection machine vision system could be implemented. Box 1 represents the water testing tunnel through which the cars enter the paint inspection stage, and circle 2 indicates the axis along which system specification data is defined. From: the author (2026).

The paint surface inspection specification list is presented in Table 5, with the data gathered through inline measurements, reference CAD models, and estimations. The upcoming car models are expected to be approximately the size of medium sized hatchbacks with a previously manufactured model used as a reference for the design. The painted surfaces will include multiple color options, and the surface finish is expected to be glossy, with a possibility of matte variants. With indexed motion positioning, the expected tolerances are ± 50 mm along the y-axis and ± 30 mm along the z-axis. The inspection area is subject to ambient lighting from fluorescent factory lighting and ceiling windows. The available installation space was measured to be approximately 15 m along the x-axis, 5 m along the y-axis, and 5+ m along the z-axis.

Table 5. Paint surface inspection specification list

Paint surface inspection specification list	
Description of the task	Detection of scratches and dents on the car paint surface at the end of general assembly. Repair is performed manually, while the system is responsible for locating defects.
Description of the expected benefit	Cost savings and potential for quality improvement
Size of the smallest feature to be detected	0.2 mm
Time from inspection to result	Instant (no buffer)
Description of the part	Vehicle's exterior paint surface
Part dimensions, height (min, max)	Height = 1,440 mm
Part dimensions, width (min, max)	Width = 1,800 mm
Part dimensions, depth (min, max)	Length = 4,420 mm
Color possibilities	Multiple (black, white, grey, silver, red, etc.)
Surface finish	Glossy or potentially matte
Corrosion, adhesives, labels, oil films, fingerprints, etc.	Possible presence of water droplets after the water testing tunnel (most water is removed by pressurized air at the end of the tunnel)
Number of different part types	Multiple
Difference between part types	Car model, panel shape, paint color and potentially surface finish
Positioning (Indexed / Manual, Continuous / Stationary)	Indexed, continuous
Stationary time / speed	Confidential
Tolerance in positioning, x	Continuously moving dimension
Tolerance in positioning, y	±50 mm
Tolerance in positioning, z	±30 mm
Information to be passed by interfaces	OK / NOK result, with possible defect locations shown in a HMI panel
Installation space (x, y, z)	x = 15+ m, y = 4.9 m, z = 3.15 m
Ambient lighting	Sun light from the factory ceiling windows and fluorescent factory illumination which could be removed or replaced with LED lights if required
Dirt / Dust	No
Shock / Vibration	No
Variations in temperature	Min 15 °C, max 35 °C, likely between 20-30 °C
Control cabinet and power supply availability	A separate control cabinet for the paint surface inspection system required

Supplier-specific machine vision system designs were developed for two major machine vision suppliers as they were the only suppliers that had developed AI-based embedded vision

systems out of the previous four contacted machine vision suppliers. Both suppliers were contacted with the designs regarding system cost and feasibility, and the final equipment selection was determined by cost efficiency. The following paint surface inspection system design is based on the selected machine vision supplier, and due to confidentiality agreements, the supplier and exact models are not disclosed. A machine vision tunnel was selected for the in-house developed solution for paint surface inspection as for a continuously moving manufacturing line the tunnel is a simpler system compared to a robot station, and it will require no moving parts. The machine vision system will receive a trigger signal to start capturing images around the car's paint surface once it is detected by a photocell sensor. The system will then process the images and send the inspection data back to the PLC, with defect locations shown on an HMI panel.

The surface area of the moving car was divided into smaller field of view sections with the widths of the sections listed as 1,100 mm for the roof, 1,100 mm for the bonnet, 665 mm for the tilted roof sections, 735 mm for the sides, 560 mm for the front and 810 mm for the rear. These field of view values were calculated based on CAD model dimensions and positioning variation. Cameras will be mounted on a steel frame structure with the working distances for the cameras listed as $WD_{\text{Roof}} = 450$ mm, $WD_{\text{Bonnet}} = 1,000$ mm, $WD_{\text{Tilted_roof}} = 450$ mm, $WD_{\text{Sides}} = 450$ mm, $WD_{\text{Front}} = 1,300$ mm, $WD_{\text{Rear}} = 1,400$ mm. The tunnel frame is bolted to the floor and manufactured from welded steel beams to prevent vibration, providing a stable imaging environment for the cameras. The fixture also functions as an illumination cover, with thin aluminium plates attached on top of the frame to block ambient light from ceiling windows and factory lighting. The structure is painted matte black to minimize reflections and it will include an inlet and an outlet for the vehicle. The CAD model of the paint surface inspection machine vision tunnel frame is presented in Figure 21.

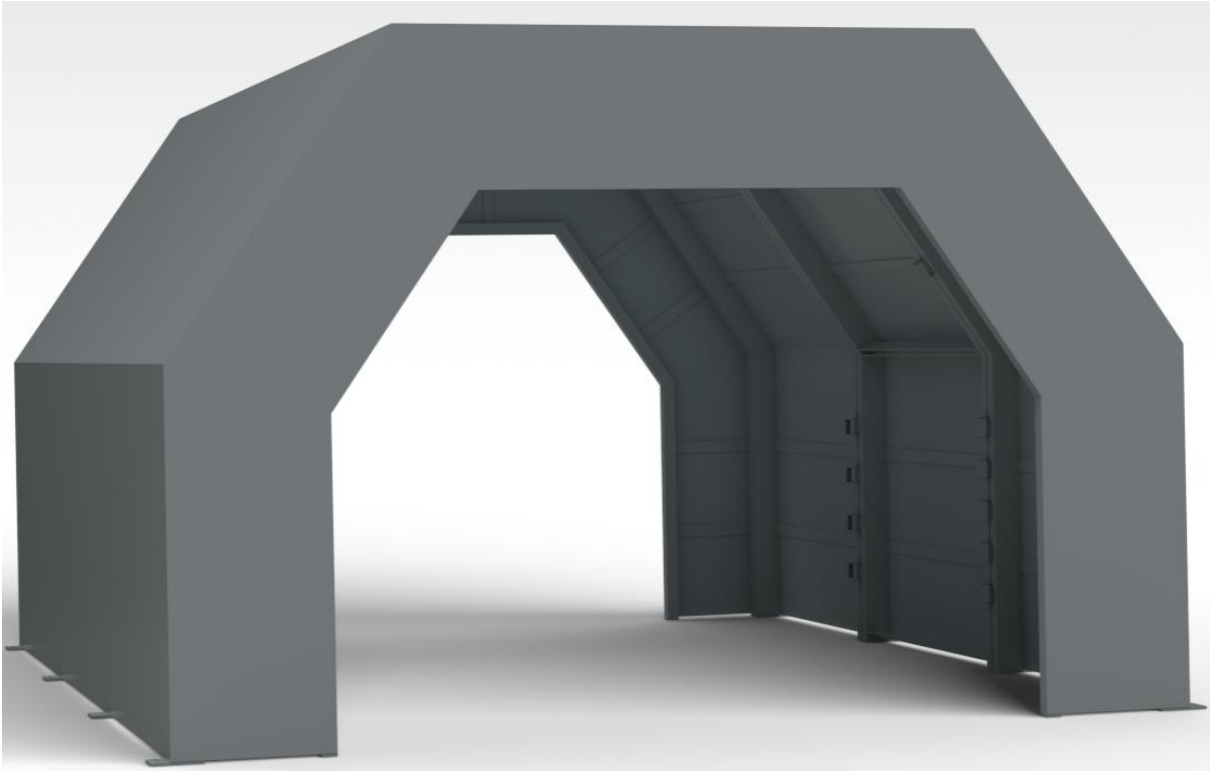


Figure 21. CAD model of the paint surface inspection machine vision tunnel frame. From: the author (2026)

Monochrome embedded vision systems were selected as color identification is not required for the task, and the high camera count benefits from the embedded vision systems. The surface scratch and dent detection is handled with AI-based camera software, as the model can be trained to detect different shape and size defects. The minimum camera resolution in the width axis was calculated for each individual camera as $R_{\text{Roof}} = 16,500$ pixels, $R_{\text{Bonnet}} = 16,500$ pixels, $R_{\text{Tilted_roof}} = 9,975$ pixels, $R_{\text{Sides}} = 11,025$ pixels, $R_{\text{Front}} = 8,250$ pixels, and $R_{\text{Rear}} = 12,150$ pixels. The resolution calculations were based on the individual field of views, three pixels to detect the smallest feature and 0.2 mm size of the smallest feature to be detected. The selection of three pixels to detect 0.2 mm scratches is based on a study conducted by Kieselbach et al. [24], where cameras with two pixels to detect 0.2 mm scratches detected almost all scratches during lab testing but missed some on silver and deep black painted surfaces. The three pixels can be expected to detect scratches larger than 0.2 mm in an industrial environment. 30 cameras (8.9 MP) along with AI-based embedded vision systems were selected from the supplier, as they provide sufficient resolution and processing capability for the application.

Lens focal lengths were calculated as 25.7 mm for the roof, 51.4 mm for the bonnet, 31.9 mm for the tilted roof sections, 28.8 mm for the sides, 51.4 mm for the front and 52.3 mm for the rear. The lens focal lengths were rounded down to available lenses from the supplier, and manufacturer MTF curves confirmed sufficient optical performance of the lenses, with a required resolution of approximately 145 line pairs per millimeter. Structurally placed white LED bar lights mounted on three rows inside the tunnel were selected as the illumination, as they should be able to sufficiently illuminate and structure both the scratches and dents. Additionally, the nearby fluorescent factory illumination can be replaced with LED tubes if required to prevent interference with imaging. The calculations and design decisions of the machine vision paint surface inspection system for the selected supplier are presented in Table 6.

Table 6. Paint surface inspection machine vision tunnel design list for the selected supplier

Paint surface inspection machine vision tunnel design list	
Field of view calculation, $FOV = S_{part} + S_{pos} + S_m + S_a$	$FOV_{Roof,X} = 1,000 \text{ mm} + 100 \text{ mm} = 1,100 \text{ mm}$ $FOV_{Bonnet,X} = 1,000 \text{ mm} + 100 \text{ mm} = 1,100 \text{ mm}$ $FOV_{Tilted_roof,X} = 565 \text{ mm} + 100 \text{ mm} = 665 \text{ mm}$ $FOV_{Side,X} = 675 \text{ mm} + 60 \text{ mm} = 735 \text{ mm}$ $FOV_{Front,X} = 490 \text{ mm} + 60 \text{ mm} = 550 \text{ mm}$ $FOV_{Rear,X} = 750 \text{ mm} + 60 \text{ mm} = 810 \text{ mm}$
Working distance determination	$WD_{Roof} = 450 \text{ mm}$, $WD_{Bonnet} = 1,000 \text{ mm}$, $WD_{Roof_tilted} = 450 \text{ mm}$, $WD_{Side} = 450 \text{ mm}$, $WD_{Front} = 1,300 \text{ mm}$, $WD_{Rear} = 1,400 \text{ mm}$,
Monochrome camera / Color camera	Monochrome cameras
Smart cameras / Embedded vision system / Industrial cameras	Embedded vision systems
System software (Traditional rule-based machine vision / AI-based machine vision)	AI-based machine vision
Camera resolution calculation, $R_c = \frac{FOV \times N_f}{S_f}$	$R_{Roof,X} = \frac{1,100 \text{ mm} \times 3 \text{ pixels}}{0.2 \text{ mm}} = 16,500 \text{ pixels}$ $R_{Bonnet,X} = \frac{1,100 \text{ mm} \times 3 \text{ pixels}}{0.2 \text{ mm}} = 16,500 \text{ pixels}$ $R_{Tilted_roof,X} = \frac{665 \text{ mm} \times 3 \text{ pixels}}{0.2 \text{ mm}} = 9,975 \text{ pixels}$ $R_{Side,X} = \frac{735 \text{ mm} \times 3 \text{ pixels}}{0.2 \text{ mm}} = 11,025 \text{ pixels}$ $R_{Front,X} = \frac{560 \text{ mm} \times 3 \text{ pixels}}{0.2 \text{ mm}} = 8,250 \text{ pixels}$ $R_{Rear,X} = \frac{810 \text{ mm} \times 3 \text{ pixels}}{0.2 \text{ mm}} = 12,150 \text{ pixels}$
Selected cameras:	30 cameras (8.9 MP) in total:

Paint surface inspection machine vision tunnel design list	
	<p>Four cameras for the roof, four cameras for the bonnet, three cameras on both sides for the tilted roof sections, three cameras on both sides for the side parts, two cameras on both sides for the front, three cameras on both sides for the rear.</p> <p>Five embedded vision systems with AI-based machine vision for computing power.</p>
Focal length calculation $f' = \frac{S_s \times WD}{FOV}$	$f'_{Roof} = \frac{4,096 \times 3.45 \times 10^{-3} \text{ mm} \times 500 \text{ mm}}{275 \text{ mm}} \approx 25.7 \text{ mm}$ $f'_{Bonnet} = \frac{4,096 \times 3.45 \times 10^{-3} \text{ mm} \times 1,000 \text{ mm}}{275 \text{ mm}} \approx 51.4 \text{ mm}$ $f'_{Tilted_roof} = \frac{4,096 \times 3.45 \times 10^{-3} \text{ mm} \times 500 \text{ mm}}{221.7 \text{ mm}} \approx 31.9 \text{ mm}$ $f'_{Side} = \frac{4,096 \times 3.45 \times 10^{-3} \text{ mm} \times 500 \text{ mm}}{245 \text{ mm}} \approx 28.8 \text{ mm}$ $f'_{Front} = \frac{4,096 \times 3.45 \times 10^{-3} \text{ mm} \times 1,000 \text{ mm}}{275 \text{ mm}} \approx 51.4 \text{ mm}$ $f'_{Rear} = \frac{4,096 \times 3.45 \times 10^{-3} \text{ mm} \times 1,000 \text{ mm}}{270 \text{ mm}} \approx 52.3 \text{ mm}$
Lens resolution calculation $\frac{LP}{mm} = \frac{10000}{2 \times S_p}$	$\frac{LP}{mm} = \frac{1}{2 \times 3.45 \times 10^{-3} \text{ mm}} \approx 145 \frac{LP}{mm}$
Selected lenses:	<p>16 lenses with a 25 mm focal length and 14 lenses with a 50 mm focal length:</p> <p>Four 25 mm focal length lenses for the roof, four 50 mm focal length lenses for the bonnet, six 25 mm focal length lenses for the tilted roof sections, six 25 mm focal length lenses for the sides, four 50 mm focal length lenses for the front, and six 50 mm focal length lenses for the rear.</p>
Illumination technique (Bright field / Dark field / Diffused lighting / Coaxial lighting / Structured lighting / diffused backlighting / Directional backlighting)	Structured zebra lighting
Illumination type (Ring light / Bar lights / Spot light / Structured light / Panel)	Bar lights
Illumination lighting type (LED / Fluorescent / Xenon)	LED
Illumination color (White / Colored / Infrared / Ultraviolet)	White
Selected illumination:	Three rows of bar lights around the tunnel
Mounting frame design	Machine vision tunnel frame bolted to the ground manufactured from welded steel beams

Paint surface inspection machine vision tunnel design list	
Equipment fixture design	Camera attached to the frame with separate fixtures which allow freedom of movement for the cameras
System control and power supply design	A separate PLC control cabinet for the paint surface inspection system with corresponding cables for the vision equipment
System specific equipment design (Illumination cover / Robotics)	Illumination cover as matte black painted aluminium panels attached on top of the machine vision tunnel frame to block ambient lighting

The profitability calculations were completed for the developed machine vision tunnel using the TCO-based profitability calculation sheet by listing the initial costs, annual costs, annual benefits and remaining value, and calculating the net present value, internal rate of return, profitability index and payback time. A yearly discount rate of 15% was applied for future cash flows in the net present value and profitability index calculations to reflect the technical complexity and associated risk of machine vision investments in the quickly transforming automotive industry. Equipment costs were provided by the supplier and the implementation costs were estimated based on system complexity and previous machine vision projects. Annual benefits were estimated based on reduced paint surface inspection time, and with the future production volume to be refined later, a five-year manufacturing contract and a reduced need for two manual inspectors personnel was used as a reference for the calculations. The remaining value of the hardware after five years was conservatively set to 0 €, as although the system could likely be reused in future production lines, future manufacturing specifications are not yet defined. The TCO-based profitability calculation results of the paint surface inspection system are presented in the results chapter.

3.5 Panel gap and flush inspection design and profitability calculation

Another machine vision application identified through interviews is the panel gap and flush inspection. Currently, Valmet Automotive's panel fittings rely on manual inspection and manual assembly. The implementation of a machine vision system presents a viable solution either to replace manual inspection or to support and speed up the assembly process. If the system automatically identifies misaligned panels, assembly work can be accelerated, as

operators would not need to manually verify all panel alignments. Feasible machine vision system concepts for the panel gap and flush inspection include a machine vision tunnel or a machine vision robot station, which could be either in-house developed or acquired as a turnkey solution from an external supplier. The start of assembly line 4, where the machine vision system for panel fittings inspection could be implemented, is presented in Figure 22.

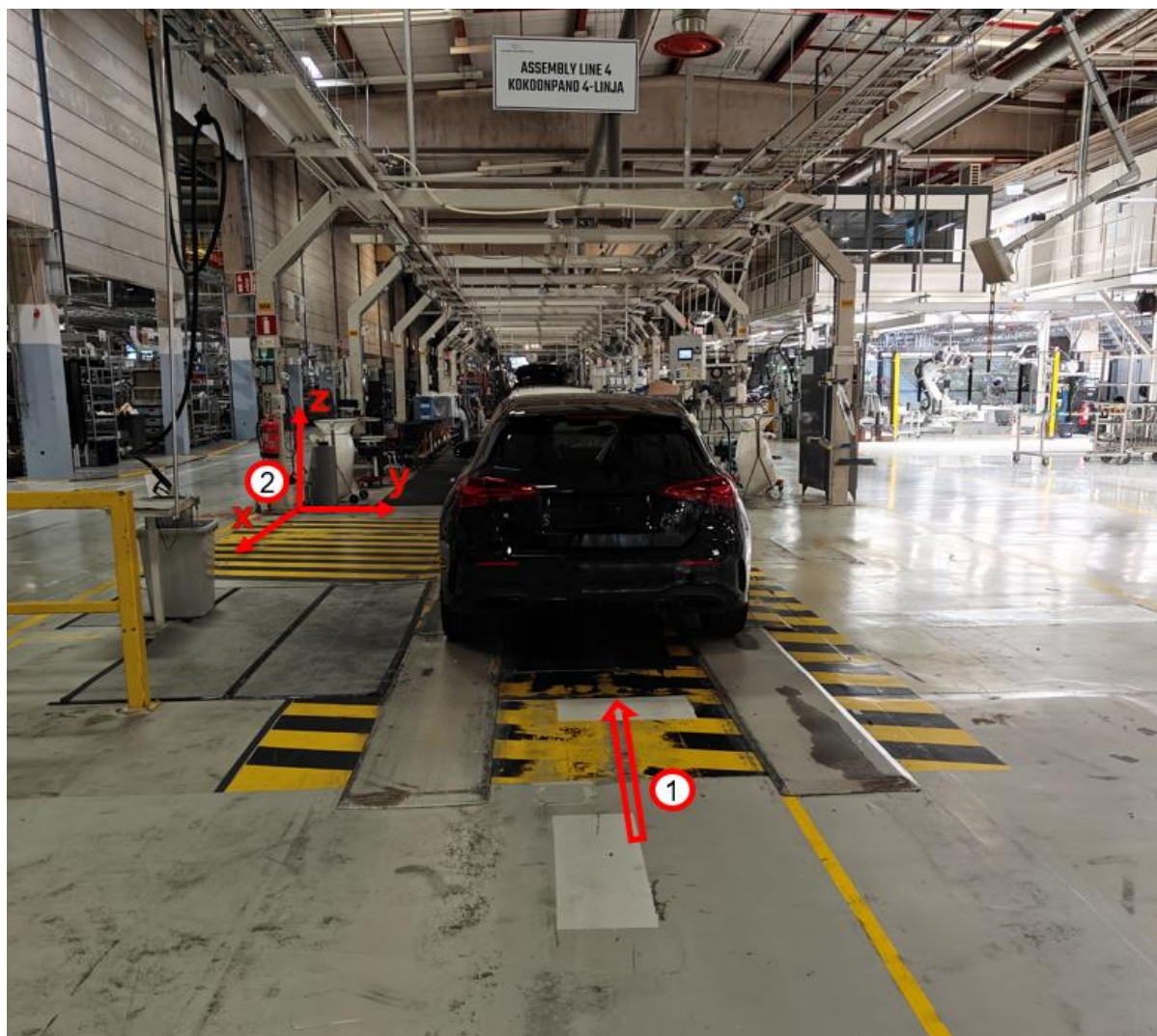


Figure 22. The start of assembly line 4, where the machine vision system could be implemented. Circle 1 indicates the direction of vehicle movement on the conveyor, and circle 2 indicates the axis along which system specification data is defined. From: the author (2026).

The panel gap and flush inspection specification list is presented in Table 7, with the data gathered through inline measurements, reference CAD models, and estimations. The upcoming car models are expected to be approximately the size of medium sized hatchbacks with a previously manufactured model used as a reference for the design. The painted surfaces

will include multiple color options, and the surface finish is expected to be glossy, with a possibility of matte variants. With indexed motion positioning, the expected tolerances are ± 30 mm along the x, y and z-axis. The inspection area is subject to ambient lighting from fluorescent factory lighting and ceiling windows. The available installation space was measured to be approximately 5 m along the x-axis, 6.5 m along the y-axis, and 3.2 m along the z-axis.

Table 7. Panel gap and flush inspection specification list

Panel gap and flush inspection specification list	
Description of the task	Measuring panel gaps and flush alignment on vehicle body panels. Detected deviations are corrected manually, while the system identifies and localizes defects.
Description of the expected benefit	Cost savings, improved process optimization data, and potential quality improvements
Size of the smallest feature to be detected	0.1 mm
Time from inspection to result	Instant (no buffer)
Description of the part	Vehicle body panel gaps around the car
Part dimensions, height (min, max)	Height = 1,440 mm
Part dimensions, width (min, max)	Width = 1,800 mm
Part dimensions, depth (min, max)	Length = 4,420 mm
Color possibilities	Multiple (black, white, grey, silver, red, etc.)
Surface finish	Glossy or potentially matte
Corrosion, adhesives, labels, oil films, fingerprints, etc.	No
Number of different part types	Multiple
Difference between part types	Car model, panel gap shape and location, paint color and possibly surface finish
Positioning (Indexed / Manual, Continuous / Stationary)	Indexed, continuous
Stationary time / speed	Confidential
Tolerance in positioning, x	± 30 mm
Tolerance in positioning, y	± 30 mm
Tolerance in positioning, z	± 30 mm
Information to be passed by interfaces	OK / NOK result, with the inspection data shown in an HMI panel
Installation space (x, y, z)	x = 5.9 m, y = 6.6 m, z = 3.55 m
Ambient lighting	Sun light from the factory ceiling windows and fluorescent factory illumination which could be removed or replaced with LED lights if required
Dirt / Dust	No

Panel gap and flush inspection specification list	
Shock / Vibration	No
Variations in temperature	Min 15 °C, max 35 °C, likely between 20-30 °C
Control cabinet and power supply availability	A separate control cabinet for the panel gap and flush inspection system required

Supplier-specific machine vision system designs were developed for four major machine vision suppliers. Each supplier was contacted with the designs regarding system cost and feasibility, and the final equipment selection was determined by cost efficiency. The following panel gap and flush inspection system design is based on the selected machine vision supplier, and due to confidentiality agreements, the supplier and exact models are not disclosed. A robot station was selected for the in-house developed solution for paint surface inspection, as the production line is not continuously moving, and laser triangulation provides a simpler approach compared to stereo vision for this application. The robot station will receive a trigger signal to start the inspection cycle once the vehicle becomes stationary. The system will then process the images and send the inspection data back to the PLC, with the inspection data shown on an HMI panel. Two spare industrial robots from Valmet Automotive's storage are used for the application and the station will be isolated with safety fencing, an interlocked safety door, and light curtains at the station inlet and outlet.

The field of view for the panel gap images was calculated as 108 mm × 91 mm based on a maximum gap size of 8 mm, positioning variation of ±30 mm, additional margins of 20 mm on both sides and adaptation to the camera aspect ratio. The camera and laser are mounted on a robot gripper, with the working distances of 160 mm for the cameras and 130 mm for the lasers. Both robot grippers will be equipped with two camera-laser pairs positioned at different angles to ensure reliable measurement of the panel gap and flush. Lasers with a wavelength of 450nm, power of 20mW, IEC safety rating class 2M and a 45° fan angle were selected for the task, as they are suitable for structuring the panel gap and flush.

Monochrome smart cameras were selected, as color information is not required for this task, and the panel gap and flush inspection will be handled with traditional rule-based camera software. The camera resolution requirement was calculated as 2,160 pixels × 1,820 pixels

based on field of view, 2 pixels to map the smallest feature and 0.1 mm size of the smallest feature. Four 5 MP rule-based machine vision cameras were selected from the supplier, as they provide sufficient resolution for the application. The lens focal length was calculated as 12.4 mm, which was rounded down to an available 12 mm lens from the supplier. The supplier's camera packages includes compatible lenses, meaning that the calculated lens resolution of 145 LP/mm was not required as the lens resolution should be able to match the camera. Additionally, the integrated camera lights will not be required with the lasers providing the illumination, and the nearby fluorescent factory illumination can be replaced with LED tubes if required to prevent them interfering with imaging. The calculations and design decisions of the machine vision gap and flush inspection system for the selected supplier are presented in Table 8.

Table 8. Panel gap and flush inspection machine vision design list for the selected supplier

Panel gap and flush inspection machine vision robot station design list	
Field of view calculation, $FOV = S_{part} + S_{pos} + S_m + S_a$	$FOV_x = 8\text{ mm} + 60\text{ mm} + 40\text{ mm} = 108\text{ mm}$ $FOV_y = 1.5\text{ mm} + 60 + 29.5\text{ mm} = 91\text{ mm}$
Working distance determination	$WD_{camera} = 160\text{ mm}$ $WD_{laser} = 130\text{ mm}$
Monochrome camera / Color camera	Monochrome
Smart cameras / Embedded vision system / Industrial cameras	Four smart cameras
System software (Traditional rule-based machine vision / AI-based machine vision)	Traditional rule-based machine vision
Camera resolution calculation, $R_c = \frac{FOV \times N_f}{S_f}$	$R_{c,x} = \frac{108\text{ mm} \times 2\text{ pixels}}{0.1\text{ mm}} \approx 2,160\text{ pixels}$ $R_{c,y} = \frac{91\text{ mm} \times 2\text{ pixels}}{0.1\text{ mm}} \approx 1,820\text{ pixels}$
Selected cameras:	Four 5 MP smart cameras with rule-based machine vision software
Focal length calculation $f' = \frac{S_s \times WD}{FOV}$	$f'_x = \frac{2,432 \times 3.45 \times 10^{-3}\text{ mm} \times 160\text{ mm}}{108\text{ mm}} \approx 12.4\text{ mm}$ $f'_y = \frac{2,048 \times 3.45 \times 10^{-3}\text{ mm} \times 160\text{ mm}}{91\text{ mm}} \approx 12.4\text{ mm}$
Lens resolution calculation $\frac{LP}{mm} = \frac{10000}{2 \times S_p}$	$\frac{LP}{mm} = \frac{1}{2 \times 3.45 \times 10^{-3}\text{ mm}} \approx 145 \frac{LP}{mm}$
Selected lenses:	Four 12 mm focal length lenses
Illumination technique (Bright field / Dark field / Diffused lighting / Coaxial lighting / Structured lighting / diffused backlighting / Directional backlighting)	Four lasers for panel gap structuring

Panel gap and flush inspection machine vision robot station design list	
Illumination type (Ring light / Bar lights / Spot light / Structured light / Panel)	-
Illumination lighting type (LED / Fluorescent / Xenon)	-
Illumination color (White / Colored / Infrared / Ultraviolet)	-
Selected illumination:	Four lasers with a wavelength of 450nm, power of 20mW, IEC safety rating class of 2M and fan angle of 45° degrees No built-in camera illumination required
Mounting frame design	-
Equipment fixture design	Robot grippers equipped with an angled adjustable camera and a straight-on laser
System control and power supply design	A separate PLC control cabinet for the panel gap and flush inspection system with corresponding cables for the vision equipment
System specific equipment design (Illumination cover / Robotics)	Robot station with two industrial robots, safety fences, interlocked safety door and light curtains on the station inlet and outlet

The profitability calculations were completed for the developed machine vision robot station using the TCO-based profitability calculation sheet by listing the initial costs, annual costs, annual benefits and remaining value, and calculating the net present value, internal rate of return, profitability index and payback time. A yearly discount rate of 15% was applied for future cash flows in the net present value and profitability index calculations to reflect the technical complexity and associated risk of machine vision investments in the quickly transforming automotive industry. Equipment costs were provided by the supplier and the implementation costs were estimated based on system complexity and previous machine vision projects. The annual benefits were estimated based on reduced panel gap and flush inspection time, and with the future production volume to be refined later, a five-year manufacturing contract and a reduced need for two manual inspectors personnel was used as a reference for the calculations. The remaining value of the hardware after five years was conservatively set to 0 €, as although the system could likely be reused in future production lines, future manufacturing specifications are not yet defined. The TCO-based profitability calculation results of the panel gap and flush inspection are presented in the results chapter.

4 Results

This chapter presents the findings of the expert interviews and the subsequent technical and economic evaluation of machine vision applications. The system designs and profitability calculations were made for the selected machine vision applications using the literature-based machine vision design approach and TCO-based profitability calculation method. The system design and profitability calculations identify the processes in Valmet Automotive's general assembly that would benefit the most from machine vision implementation and provide insights into the feasibility of these systems. Profitability calculations were conducted for the plug inspection, paint surface inspection, and panel gap and flush inspection, but not for the tire distribution system, as it would be required in cases involving same size tires across different car models. The designed machine vision tire distribution system on the tire conveyor presents a viable solution alongside the other machine vision application designs, with the feasibility of the designs confirmed with supplier meetings.

4.1 Interviews

The goal of the interviews was to identify potential machine vision applications and design considerations from the perspective of different departments. From the advanced engineering department, a lead project engineer was interviewed. The identified applications in the Valmet Automotive general assembly included inspection and positioning in automated cells, assembly verification of plugs on the underbody, and paint surface and panel gap inspection. The primary challenge in machine vision system implementation in the general assembly of Valmet Automotive was noted as illumination due to the factory floor having fluorescent lighting and shadowed areas. Another identified challenge was the cost of machine vision systems, as short payback would be required for project approval. One proposed solution to reduce costs was using cost-effective Chinese-based machine vision cameras. Although when using Chinese-based machine vision camera suppliers, the credibility should be thoroughly evaluated.

From the manufacturing engineering department, a senior project engineer from the general assembly was interviewed. The identified applications included positioning in new automated cells for assembly tightening, assembly verification of plugs on the underbody, paint surface and panel gap inspection, and assembly order verification of tightening tools. Challenges

related to assembly order verification included the difficulty of distinguishing closely positioned bolts and potential camera blind spots in a production environment. Another challenge was the limited in-house machine vision expertise at Valmet Automotive. Sufficient expertise within the manufacturing engineering and maintenance departments would have to be ensured to avoid reliance on external suppliers.

From the process planning department, four process planners from general assembly were interviewed. The identified applications included inspection in automated cells, assembly verification of plugs on the underbody, and inspection of paint surface and panel gaps. The challenges identified with machine vision implementation were related to system functionality, cost, and limited space to work around inconsistent lighting. An additional consideration was to ensure that Valmet Automotive has enough expertise in machine vision to troubleshoot system errors during production.

From the quality department, a quality engineer and two senior quality engineers from general assembly were interviewed. The identified applications included paint surface and panel gap inspection, and assembly verification of plugs on the underbody. The identified challenges were related to illumination setup and project funding, as machine vision projects would require a short payback period for project approval. A key requirement from the quality department was the automatic transfer of data from machine vision systems to Valmet Automotive's data management systems. This requirement is particularly important when evaluating turnkey machine vision solutions from external suppliers.

From the maintenance department, the manager, senior automation engineer and senior maintenance engineer from general assembly were interviewed. An identified application for machine vision would be to inspect equipment wear to reduce repair costs and downtime. However, no specific tasks with clear expected profitability for such applications were identified in the general assembly. The challenge identified with machine vision implementation was the lack of machine vision expertise in the maintenance department. In case new machine vision systems are implemented, training would be required for camera software setup and for integrating machine vision systems and PLCs.

From the production department, two process operators were interviewed. The identified applications included inspection in automated cells, and detection of plugs at door pre-assembly and on the underbody. A key implementation consideration was to use testing equipment from the supplier and conduct thorough testing prior to procurement. This would reduce the risk of acquiring unsuitable equipment. Additionally, sufficient final test runs after procurement were emphasized to ensure system functionality before system handover to production. The interview results of Valmet Automotive personnel are combined in Table 9.

Table 9. The interview results of Valmet Automotive personnel regarding machine vision applications, implementation challenges and design considerations.

Interview results of Valmet Automotive personnel			
Department and personnel	Applications	Challenges	Design considerations
Advanced engineering department -lead project engineer	Inspection and positioning in automated cells Assembly verification of plugs on the underbody Paint surface and panel gap inspection	Illumination due to fluorescent factory lights and many shadowed areas High initial costs of machine vision systems	Using cheaper cost-effective cameras possibly from Chinese manufacturers. Although when using Chinese based camera suppliers, the credibility should be thoroughly evaluated
Manufacturing engineering department -senior project engineer of general assembly	Positioning in new automated cells for assembly tightening Assembly verification of plugs on the underbody Paint surface and panel gap inspection Assembly order verification of tightening tools	Limited in-house machine vision expertise at Valmet Automotive.	Ensuring that manufacturing engineering and maintenance departments have sufficient expertise in machine vision
Process planning department -four process planners of general assembly	Inspection in automated cells Assembly verification of plugs on the underbody Paint surface and panel gaps inspection	Functionality and costs of machine vision systems Limited space in the assembly area to work around inconsistent lighting	Ensuring that Valmet Automotive has enough expertise in machine vision to fix system errors during production
Quality department -quality engineer and two senior quality engineers of general assembly	Assembly verification of plugs on the underbody Paint surface and panel gap inspection	Sufficient illumination set up Project funding as the projects would require a short payback time for project approval	Having the data from the machine vision system automatically transferred to the data management systems of Valmet Automotive

Interview results of Valmet Automotive personnel			
Maintenance department -manager, senior automation engineer and senior maintenance engineer of general assembly	Equipment wear inspection to reduce repair costs and downtime. However, no specific tasks with probable profitability were identified	Limited machine vision expertise in the maintenance department	Training personnel with the machine vision camera software setup in case new machine vision systems are implemented
Production department -two process operators of general assembly	Inspection in automated cells Assembly verification of plugs on the underbody and at the door preassembly	Sufficient testing of the machine vision system	Conducting thorough testing with the supplier's testing equipment before procurement and having sufficient final test runs before handover to production

The key takeaways from the interviews were the identified applications in the general assembly of Valmet Automotive and the key factors to be considered in the design and implementation of machine vision systems. The identified machine vision applications from the interviews included plug installation inspection on the door preassembly and underbody, and paint surface and panel fittings inspection with machine vision tunnels or robot stations. Plug installation inspection would prevent time-consuming rework caused by missing plugs, and the paint and panel fitting inspections with machine vision would remove the need for monotonous and time-consuming manual inspection. Additionally, the plug installation inspection on the door preassembly could potentially be performed using an existing machine vision camera located at the end of door preassembly, which already verifies that the doors are properly attached to the conveyor hangers. An additional previously identified machine vision application at Valmet Automotive is the tire distribution on the tire conveyor with machine vision cameras to ensure feasibility of the conveyor in the future.

Fastener assembly verification with tool positioning using AI-based machine vision cameras appears a promising solution. However, further information on new car models and their requirements is needed before system design can proceed. The addition of new automated cells made possible with machine vision is also a promising application, but it would require major changes done to the manufacturing lines. Both fastener assembly verification with tool positioning and the addition of new automated cells remain potential future projects requiring further evaluation. A key noted design considerations from the interviews was to prioritize

applications with high returns while seeking opportunities to minimize costs. Additional implementation considerations include conducting thorough testing, particularly with the illumination, and ensuring that relevant Valmet Automotive personnel have sufficient machine vision expertise.

4.2 Plug installation inspection on the underbody

TCO-based profitability calculations were conducted for the plug installation inspection machine vision system, with the profitability calculation results presented in Table 10. The initial costs were calculated as 10,610 €, annual costs as 100 €, annual benefits as 6,500 € and remaining value as 0 €. The net present value was calculated as 10,840 €, internal rate of return as 53%, profitability index as 1.99, and payback time as 20 months. The results indicate profitability with a reference data of a five-year manufacturing contract with an annual production volume of 30,000 vehicles, assuming rework levels are consistent with the reported rework done with previous manufacturing lines.

Table 10. Plug installation inspection TCO-based profitability calculation list

Plug installation inspection TCO-based profitability calculation list	
Initial costs: $C_0 = 10,610$ €	
Testing work (50 €/h)	800 €
Design work left (50 €/h)	200 €
Cameras	4,270 €
Lenses	Included in the camera package
Illumination	Included in the camera package
Connection cables	600 €
System specific hardware (interface panels, industrial robots, lighting covers, etc.)	Camera fixture materials and manufacturing: 500 €
Software licenses	Included in the camera package
Spare parts	-
Hardware installation (30 €/h)	240 €
PLC coding (50 €/h)	1,200 €
Camera software setup (50 €/h)	2,000 €
Test run materials	-
Final test runs (50 €/h)	400 €
Documentation (50 €/h)	100 €
Personnel training	300 €

Plug installation inspection TCO-based profitability calculation list							
Annual costs: $C_y = 100 \text{ €}$							
Electricity	10 €						
System modification work due to product change	-						
Maintenance and troubleshooting work (30 €/h)	90 €						
Component replacement	-						
Line stoppages	-						
Annual benefits: $B_y = 6,500 \text{ €}$, removed chance of missing plugs ending in the final product							
Savings from reduced manual work (30 €/h)	Reduced inspection time: $\frac{20 \text{ s}}{3600} \times 30 \frac{\text{€}}{\text{h}} \times 30,000 = 5,000 \text{ €}$ Reduced rework based on previous reported rework done due to missing plugs: 1,500 €						
Quality improvement	Removed chance of missing plugs ending up in the final product to the customer						
Safety improvement	-						
Increased data for production development	-						
Remaining value: $B_r = 0 \text{ €}$							
Value of remaining hardware	0 €						
Costs of equipment removal	-						
TCO-based profitability calculation:							
Year	1	2	3	4	5	6	7
Initial costs, C_0	10,610€						
Annual costs, C_t	100€	100€	100€	100€	100€		
Annual benefits, B_t	6,500€	6,500€	6,500€	6,500€	6,500€		
Remaining value, B_r					0€		
$NPV(15\%) = \sum_{t=1}^n \frac{B_t - C_t}{(1.15)^t} + \frac{B_r}{(1.15)^n} - C_0$			$NPV(15\%) = \sum_{t=1}^5 \frac{6,500 \text{ €} - 100 \text{ €}}{(1.15)^t} - 10,610 \text{ €}$ $\approx 10,840 \text{ €}$				
$\sum_{t=1}^n \frac{B_t - C_t}{(IRR)^t} + \frac{B_r}{(IRR)^n} - C_0 = 0$			$\sum_{t=1}^5 \frac{6,500 - 100}{(IRR)^t} - 10,610 = 0 \rightarrow IRR \approx 53\%$				
$PI(15\%) = \frac{\sum_{t=1}^n \frac{B_t}{(1.15)^t} + \frac{B_r}{(1.15)^n}}{C_0 + \sum_{t=1}^n \frac{C_t}{(1.15)^t}}$			$PI(15\%) = \frac{\sum_{t=1}^5 \frac{6,500}{(1.15)^t}}{10,610 + \sum_{t=1}^5 \frac{100}{(1.15)^t}} \approx 1.99$				
$PB_m = \frac{C_0}{B_t - C_t} \times 12$			$PB_m = \frac{10,610}{6,500 - 100} \times 12 \approx 20 \text{ months}$				

4.3 Paint surface inspection

TCO-based profitability calculations were conducted for the developed paint surface inspection machine vision tunnel, with the profitability calculation results presented in Table 11. The initial costs were calculated as 150,380 €, annual costs as 1,420 €, annual benefits as 100,000 € and remaining value as 0 €. The net present value was calculated as 180,080 €, internal rate of return as 59 %, profitability index as 2.16, and payback time as 18 months. The profitability calculations indicate high profitability with the reference data of a five-year manufacturing contract and a reduced need for two manual inspectors personnel.

Table 11. Paint surface inspection machine vision tunnel TCO-based profitability calculation list

Paint surface inspection machine vision tunnel TCO-based profitability calculation list	
Initial costs: $C_0 = 150,380$ €	
Testing work (50 €/h)	4,000 €
Design work left (50 €/h)	800 €
Cameras (including embedded vision systems)	97,950 €
Lenses	7,530 €
Illumination	10,500 €
Connection cables	2,500 €
System specific hardware (interface panels, industrial robots, lighting covers, etc.)	Machine vision tunnel frame materials and manufacturing: 4,000 €
Software licenses	Included in the camera package
Spare parts	800 €
Hardware installation (30 €/h)	2,400 €
PLC coding (50 €/h)	6,000 €
Camera software setup (50 €/h)	10,000 €
Test run materials	-
Final test runs (50 €/h)	2,000 €
Documentation (50 €/h)	400 €
Personnel training	1,500 €
Annual costs: $C_y = 1,420$ €	
Electricity	820 €
System modification work due to product change	-
Maintenance and troubleshooting work (30 €/h)	600 €

Paint surface inspection machine vision tunnel TCO-based profitability calculation list							
Component replacement	-						
Line stoppages	-						
Annual benefits: $B_y = 100,000 \text{ €}$							
Savings from reduced manual work (50,000 € / personnel annually)	100,000 €						
Quality improvement	-						
Safety improvement	-						
Increased data for production development	-						
Remaining value: $B_r = 0 \text{ €}$							
Value of remaining hardware	0 €						
Costs of equipment removal	-						
TCO-based profitability calculation:							
Year	1	2	3	4	5	6	7
Initial costs, C_0	150,380€						
Annual costs, C_t	1,420€	1,420€	1,420€	1,420€	1,420€		
Annual benefits, B_t	100,000€	100,000€	100,000€	100,000€	100,000€		
Remaining value, B_r					0€		
$NPV(15\%) = \sum_{t=1}^n \frac{B_t - C_t}{(1.15)^t} + \frac{B_r}{(1.15)^n} - C_0$			$NPV(15\%) = \sum_{t=1}^5 \frac{100,000\text{€} - 1,420\text{€}}{(1.15)^t} - 150,380\text{€} \approx 180,080 \text{ €}$				
$\sum_{t=1}^n \frac{B_t - C_t}{(IRR)^t} + \frac{B_r}{(IRR)^n} - C_0 = 0$			$\sum_{t=1}^5 \frac{100,000 - 1,420}{(IRR)^t} - 150,380 = 0$ $\rightarrow IRR \approx 59\%$				
$PI(15\%) = \frac{\sum_{t=1}^n \frac{B_t}{(1.15)^t} + \frac{B_r}{(1.15)^n}}{C_0 + \sum_{t=1}^n \frac{C_t}{(1.15)^t}}$			$PI(15\%) = \frac{\sum_{t=1}^5 \frac{100,000}{(1.15)^t}}{150,380 + \sum_{t=1}^5 \frac{1,420}{(1.15)^t}} \approx 2.16$				
$PB_m = \frac{C_0}{B_t - C_t} \times 12$			$PB_m = \frac{150,380}{100,000 - 1,420} \times 12 \approx 18 \text{ months}$				

4.4 Panel gap and flush inspection

TCO-based profitability calculations were conducted for the developed panel gap and flush inspection machine vision robot station, with the profitability calculation results presented in Table 12. The initial costs were calculated as 41,220 €, annual costs as 4,980 €, annual benefits as 100,000 € and remaining value as 0 €. The net present value was calculated as 277,300 €, internal rate of return as 230%, profitability index as 5.79, and payback time as 5

months. The profitability calculations indicate significant profitability with the reference data of a five-year manufacturing contract and a reduced need for two manual inspectors personnel.

Table 12. Panel gap and flush inspection robot station TCO-based profitability calculation list

Panel gap and flush inspection robot station TCO-based profitability calculation list	
Initial costs: $C_0 = 41,220$ €	
Testing work (50 €/h)	2,000 €
Design work left (50 €/h)	2,000 €
Cameras	12,760 €
Lenses	Included in the camera package
Illumination	-
Connection cables	500 €
System specific hardware (interface panels, industrial robots, lighting covers, etc.)	Lasers and laser equipment 5,260 € Robot gripper materials and manufacturing 600€ Robot programming 4,000 €
Software licenses	Included in the camera package
Spare parts	100 €
Hardware installation (30 €/h)	3,600 €
PLC coding (50 €/h)	2,000 €
Camera software setup (50 €/h)	6,000 €
Test run materials	-
Final test runs (50 €/h)	800 €
Documentation (50 €/h)	400 €
Personnel training	1,200 €
Annual costs: $C_y = 4,980$ €	
Electricity	880 €
System modification work due to product change	-
Maintenance and troubleshooting work (30 €/h)	900 €
Component replacement	500 €
Line stoppages	2,700 €
Annual benefits: $B_y = 100,000$ €, increased data for panel adjustment earlier in the process	
Savings from reduced manual work (50,000 € / personnel annually)	100,000 €
Quality improvement	-
Safety improvement	-

Panel gap and flush inspection robot station TCO-based profitability calculation list							
Increased data for production development				Increased data for panel adjustment earlier in the process			
Remaining value: $B_r = 0 \text{ €}$							
Value of remaining hardware				0 €			
Costs of equipment removal				-			
TCO-based profitability calculation:							
Year	1	2	3	4	5	6	7
Initial costs, C_0	41,220€						
Annual costs, C_t	4,980€	4,980€	4,980€	4,980€	4,980€		
Annual benefits, B_t	100,000€	100,000€	100,000€	100,000€	100,000€		
Remaining value, B_r					0€		
$NPV(15\%) = \sum_{t=1}^n \frac{B_t - C_t}{(1.15)^t} + \frac{B_r}{(1.15)^n} - C_0$				$NPV(15\%) = \sum_{t=1}^5 \frac{100,000 \text{ €} - 4,980 \text{ €}}{(1.15)^t} - 41,220 \text{ €} \approx 277,300 \text{ €}$			
$\sum_{t=1}^n \frac{B_t - C_t}{(IRR)^t} + \frac{B_r}{(IRR)^n} - C_0 = 0$				$\sum_{t=1}^5 \frac{100,000 - 4,980}{(IRR)^t} - 41,220 = 0$ $\rightarrow IRR \approx 230\%$			
$PI(15\%) = \frac{\sum_{t=1}^n \frac{B_t}{(1.15)^t} + \frac{B_r}{(1.15)^n}}{C_0 + \sum_{t=1}^n \frac{C_t}{(1.15)^t}}$				$PI(15\%) = \frac{\sum_{t=1}^5 \frac{100,000}{(1.15)^t}}{41,220 + \sum_{t=1}^5 \frac{4,980}{(1.15)^t}} \approx 5.79$			
$PB_m = \frac{C_0}{B_t - C_t} \times 12$				$PB_m = \frac{41,220}{100,000 - 4,980} \times 12 \approx 5 \text{ months}$			

4.5 Synthesis of results

The systematic machine vision design approach and TCO-based profitability calculation method developed in this study proved effective in the technical and economic evaluation of machine vision systems. Several feasible machine vision applications were identified at Valmet Automotive, specifically tire distribution on the tire conveyor, plug installation inspection on the underbody, paint surface inspection, and panel gap and flush inspection. Of these, the panel gap and flush inspection emerged as the most profitable application. The high profitability of panel gap inspection is driven by the replacement of manual inspection roles combined with relatively moderate initial investment. The initial investment is significantly reduced due to Valmet Automotive having spare industrial robots available in storage. While the paint surface inspection tunnel requires a substantially higher initial investment, it remains

highly profitable due the replacement of manual inspection roles. The plug installation inspection also proved profitable with the reference calculation data, as although its annual net benefits are lower, the required initial investment is minimal. A comparative synthesis of the profitability results is detailed in Table 13.

Table 13. Profitability summary of machine vision applications

Profitability summary of machine vision applications						
Application	Initial investment C_0	Annual net benefit $B_y - C_y$	NPV (15%)	IRR	PI (15%)	Payback time
Plug installation inspection	10,610€	6,400€	10,840€	53%	1.99	20 months
Paint surface inspection	150,380€	98,580€	180,080€	59%	2.16	18 months
Panel gap and flush inspection	41,220€	95,020€	277,300€	230%	5.79	5 months

The research questions formulated at the beginning of this study are answered as follows:

- Which processes in the automotive manufacturing general assembly would benefit most from machine vision implementation? Panel gap and flush inspection emerged as the most profitable application, followed by paint surface inspection and plug installation inspection, respectively.
- How can cross-domain design principles be applied to systematically design machine vision systems? Cross-domain design principles can be applied by using a structured framework to bridge separate engineering disciplines. In this study, this is achieved by first identifying all technical requirements using the machine vision system specification list and then systematically addressing them through the machine vision design list.
- How can TCO-based profitability calculation methods be applied to evaluate the costs and profitability of machine vision systems? TCO-based profitability calculation methods for machine vision systems are applied by shifting the evaluation from initial procurement costs to a comprehensive lifecycle perspective. In this study, this is achieved by utilizing the developed TCO-based profitability calculation list, in which all costs and benefits are accounted for over the lifecycle of the machine vision system and multiple project profitability metrics are applied.

5 Conclusions

This study developed a systematic literature-based machine vision design approach and a TCO-based profitability calculation method for economical evaluation of machine vision systems. The study included expert interviews with Valmet Automotive personnel which were used to identify feasible machine vision applications; tire distribution on the tire conveyor, plug installation inspection on the underbody, paint surface inspection, and panel gap and flush inspection. The design approach and TCO-based profitability calculation method were applied to the selected applications to determine which processes in the automotive manufacturing general assembly would benefit most from machine vision implementation.

The developed systematic literature-based machine vision design approach demonstrated effectiveness in the design of machine vision systems. The systematic identification of all relevant system requirements and specifications, as outlined in the machine vision system specification list found in Appendix 1, significantly simplified the design process of the systems. Furthermore, addressing all cross-domain design aspects of machine vision systems in a systematic manner, as presented in the machine vision design list found in Appendix 2, streamlined the design process and enabled the development of comprehensive system designs. The developed machine vision system TCO-based profitability calculation list presented in Appendix 3 proved effective in the economic evaluation of the designed machine vision solutions. By systematically accounting all costs and benefits over the entire lifecycle of a machine vision project and applying multiple relevant project profitability metrics, the profitability of different machine vision applications could be assessed in a clear and structured manner.

Based on the TCO-based profitability calculations, the panel gap and flush inspection robot station showed the greatest profitability and would benefit the most from implementation, followed by the paint surface inspection machine vision tunnel and the plug inspection system. The tire distribution machine vision system is required for the tire conveyor to operate in cases involving identical tire sizes across different vehicle models. The exact profitability of the systems depends on the production volumes of future manufacturing contracts, but the designed machine vision systems indicated very high profitability with

reference calculation data. This is highlighted by the combined net present value of approximately 468,000 € for the designed applications. In the future as new manufacturing contracts are signed, the designs can be updated with new product data and profitability calculations can be adjusted with actual production volumes to determine precise profitability. If the updated calculations still demonstrate high profitability, the designed applications can be implemented to significantly reduce manufacturing costs, improve quality, and increase data availability for process optimization.

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Appendices

Appendix 1: Machine vision system specification list

Machine vision system specification list	
Description of the task	
Description of the expected benefit	
Size of the smallest feature to be detected	
Time from inspection to result	
Description of the part	
Part dimensions, height (min, max)	
Part dimensions, width (min, max)	
Part dimensions, depth (min, max)	
Color possibilities	
Surface finish	
Corrosion, adhesives, labels, oil films, fingerprints, etc.	
Number of different part types	
Difference between part types	
Positioning (Indexed / Manual, Continuous / Stationary)	
Stationary time / speed	
Tolerance in positioning, x	
Tolerance in positioning, y	
Tolerance in positioning, z	
Information to be passed by interfaces	
Installation space (x, y, z)	
Ambient lighting	
Dirt / Dust	
Shock / Vibration	
Variations in temperature	
Control cabinet and power supply availability	

Appendix 2: Machine vision system design list

Machine vision system design list	
Field of view calculation, $FOV = S_{part} + S_{pos} + S_m + S_a$	
Working distance determination	
Monochrome camera / Color camera	
Smart cameras / Embedded vision system / Industrial cameras	
System software (Traditional rule-based machine vision / AI-based machine vision)	
Camera resolution calculation, $R_c = \frac{FOV \times N_f}{S_f}$	
Selected cameras:	
Focal length calculation $f' = \frac{S_s \times WD}{FOV}$	
Lens resolution calculation $\frac{LP}{mm} = \frac{10000}{2 \times S_p}$	
Selected lenses:	
Illumination technique (Bright field / Dark field / Diffused lighting / Coaxial lighting / Structured lighting / diffused backlighting / Directional backlighting)	
Illumination type (Ring light / Bar lights / Spot light / Structured light / Panel)	
Illumination lighting type (LED / Fluorescent / Xenon)	
Illumination color (White / Colored / Infrared / Ultraviolet)	
Selected illumination:	
Mounting frame design	
Equipment fixture design	
System control and power supply design	
System specific equipment design (Illumination cover / Robotics)	

Appendix 3: Machine vision system TCO-based profitability calculation list

Machine vision system TCO-based profitability calculation list							
Initial costs: $C_0 =$							
Testing work (x e/h)							
Design work (x e/h)							
Cameras							
Lenses							
Illumination							
Connection cables							
System specific hardware (interface panels, industrial robots, lighting covers, etc.)							
Software licenses							
Spare parts							
Hardware installation (x e/h)							
PLC coding (x e/h)							
Camera software setup (x e/h)							
Test run materials							
Final test runs (x e/h)							
Documentation (x e/h)							
Personnel training							
Annual costs: $C_y =$							
Electricity							
System modification work due to product change (x e/h)							
Maintenance work (x e/h)							
Component replacement							
Line stoppages (x e/h)							
Annual benefits: $B_y =$							
Savings from reduced manual work (x e/personnel)							
Quality improvement							
Safety improvement							
Increased data for production development							
Remaining value: $B_r =$							
Value of remaining hardware							
Costs of equipment removal							
TCO-based profitability calculation:							
Year	1	2	3	4	5	6	7

Machine vision system TCO-based profitability calculation list							
Initial costs, C_0							
Annual costs, C_t							
Annual benefits, B_t							
Remaining value, B_r							
$NPV(15\%) = \sum_{t=1}^n \frac{B_t - C_t}{(1.15)^t} + \frac{B_r}{(1.15)^n} - C_0$							
$\sum_{t=1}^n \frac{B_t - C_t}{(IRR)^t} + \frac{B_r}{(IRR)^n} - C_0 = 0$							
$PI(15\%) = \frac{\sum_{t=1}^n \frac{B_t}{(1.15)^t} + \frac{B_r}{(1.15)^n}}{C_0 + \sum_{t=1}^n \frac{C_t}{(1.15)^t}}$							
$PB_m = \frac{C_0}{B_t - C_t} \times 12$							