

Review

Machine vision in manufacturing SMEs: a review

Jonas Werheid¹ · Hannes Behnen¹ · Jan-Henrik Woltersmann¹ · Shengjie He¹ · Tobias Hamann¹ · Anas Abdelrazeq¹ · Robert H. Schmitt^{1,2}

Received: 5 February 2025 / Accepted: 9 April 2025

Published online: 19 April 2025

© The Author(s) 2025 [OPEN](#)

Abstract

Automating manufacturing tasks, such as quality control, fault detection, part classification, and inventory management with machine vision systems can significantly improve process efficiency, accuracy, and productivity. As a result, the machine vision technology market is expanding, largely driven by its applications in manufacturing across both hardware and software sectors. Nevertheless, small- and medium-sized enterprises (SMEs) face distinct challenges in the implementation of such systems due to their human, technical, and organizational constraints. An overview of the current state of research and practical insights is essential to address these constraints and guide future developments. Although some surveys and interviews have been conducted, no comprehensive review outlines scientific literature on research methods and initiatives related to the characteristics and challenges of adopting machine vision systems in industrial SMEs. Therefore, we present a systematic literature review to identify applications, challenges and proposed approaches for machine vision and its adoption in industrial SMEs, analyzing 770 articles. The review highlights quality control as the prominent application, while primary challenges for SMEs include limited investment capacity, labor and expertise shortages, and high-variety, low-volume production, which often leads to insufficient data for training algorithms. Furthermore, the review identifies approaches involving low-cost hardware, open-source software, and intuitive-to-use systems as potential solutions to these challenges. Although many articles contribute to highly specific problems of SMEs, we identified a lack of broader applicable interdisciplinary approaches to integrate machine vision. This article outlines challenges and initiatives for adopting machine vision across different applications to enhance value generation for industrial SMEs facing specific challenges. Future research can leverage our findings to develop industrial solutions or explore new research directions in this domain.

Article highlights

- Machine vision fosters efficiency and quality in SMEs production
- High costs and lack of skills are the main challenges in vision technology adoption
- Lack of integrated frameworks calls for holistic solutions tackling cost, skills, data, and production variety

Keywords Machine vision · Manufacturing · SME · Technology transfer · Review

✉ Jonas Werheid, jonas.werheid@rwth-aachen.de | ¹Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Campus-Boulevard 30, Aachen, Germany. ²Fraunhofer Institute for Production Technology IPT, Fraunhofer-Gesellschaft, Steinbachstraße 17, Aachen, Germany.



1 Introduction

Manufacturing companies digitalize and automate their processes to enhance efficiency, accuracy, and productivity [1]. Key automation tasks such as quality control, fault detection, part classification, and inventory management are increasingly handled by machine vision systems [2–5]. As these systems become integral to modern manufacturing environments, the machine vision technology market expands rapidly [6]. Market growth rates of over 10 percent until 2030 are expected with manufacturing as the dominant industry in market share [7].

Despite the ongoing adoption of machine vision technologies in industry, small- and medium-sized enterprises (SMEs) face unique challenges in integrating these technologies. SMEs often operate under significant human, technical, and organizational constraints, which contradict the requirements of implementing advanced technologies [8]. Given their critical role in economies like Germany and the United States, where SMEs account for 97.3 percent and 98.6 percent of all manufacturing companies respectively, addressing these barriers is essential to maintaining competitiveness and fostering innovation in the manufacturing sector [9, 10].

Articles have explored various technical aspects of machine vision systems, including algorithm advancements, hardware design, and software development [11, 12]. However, most of this research does not consider the unique challenges SMEs face. While some literature addresses specific aspects of these challenges, such as the limited investment capacities of SMEs [13], a comprehensive understanding of how these challenges interplay in the context of machine vision adoption remains understudied. Despite presented interviews on adopting machine vision technologies [14], no systematic review has specifically addressed the unique characteristics, challenges, and solution approaches faced by industrial SMEs. Such a review that synthesizes existing research and identifies the intersected area of machine vision, manufacturing applications, and technology transfer for SMEs could contribute valuable insights for researchers and practitioners, guiding future developments and facilitating more effective adoption of machine vision technologies in industrial SMEs.

To address this gap, a systematic literature review based on the PRISMA method will be conducted [15]. The review aims to answer the following research questions:

1. What are the key application domains and tasks in industrial machine vision for SMEs?
2. What challenges do scientific articles identify in the use of machine vision systems for SMEs?
3. What approaches and solutions are presented to address these challenges?

The structure begins with fundamentals in Chapter 2, followed by the review methodology and literature analysis in Chapter 3. Chapter 4 presents the findings to the research questions, and Chapter 5 concludes with limitations and future research directions.

2 Fundamentals

This article focuses on the intersection of three domains: machine vision, industrial manufacturing, and technology adoption for industrial SMEs. To facilitate understanding, Sect. 2.1 provides an overview of the fundamentals of machine vision as applied in industrial manufacturing, while Sect. 2.2 addresses the adoption of technology by SMEs, highlighting the interdependencies among human skills, technological requirements, and organizational structures.

2.1 Machine vision in industrial manufacturing

Machine vision, also referred to as the utilization of computer vision in industry, leverages various technologies, including optics, imaging, sensors, and software algorithms, mostly to automate image analysis e.g. for inspection and process control. Machine vision systems are widely used in industrial manufacturing sectors such as automotive, electronics, and aerospace [16–18]. In these industries, they are integral to automating key functions like quality control, inventory management, and part tracking, enhancing efficiency and precision throughout production processes [5, 19, 2]. A typical machine vision system involves multiple hardware and software components to capture

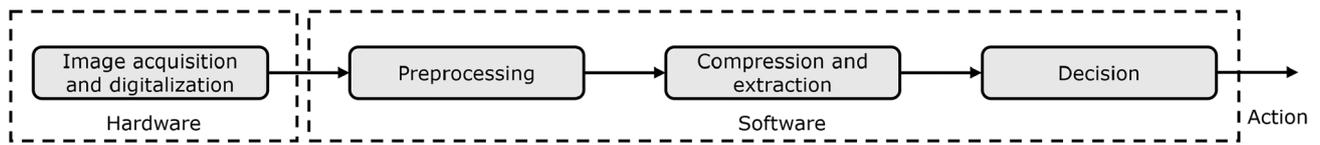
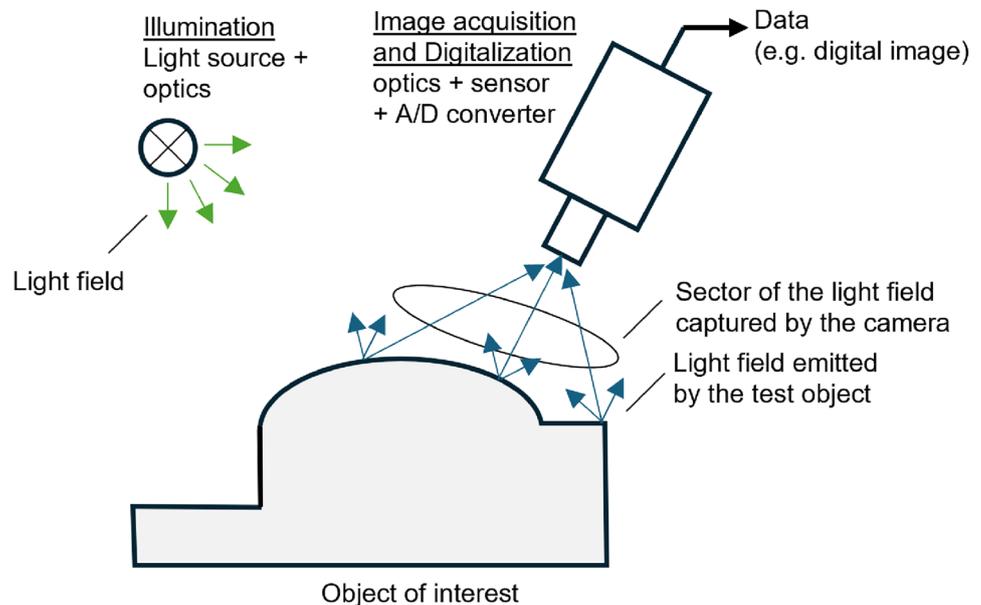


Fig. 1 Process chain of machine vision systems in industrial applications based on Beyerer et al. [20]

Fig. 2 Image acquisition of the object of interest based on Beyerer et al. [20]



and analyze images. Beyerer et al. outline the process chain of machine vision systems in industrial applications as comprising image acquisition and digitization, preprocessing, information compression and extraction, followed by decision-making that leads to action. This process is illustrated in Fig. 1 with a flowchart [20].

The first step in the machine vision chain is image acquisition and digitalization. It describes the process in which a camera captures optical image data of a scene and its environment (such as lighting), along with features like the objects of interest, which is then converted into a digital image by analog-to-digital converters [21]. Figure 2 illustrates the sensing process, showing the camera system, illumination setup, the object under inspection, and the optical geometry [20].

After image acquisition and digitalization, the digitalized images are usually preprocessed. Image preprocessing involves improving the image quality according to the specific requirements of the corresponding task [22]. This can be noise reduction, image resizing, or cropping to proper frames [22, 23].

Along with preprocessed image data, compression, and feature extraction are carried out. Compression describes the process of reducing the image size without significant loss of quality to make transmitting and storing large volumes of images easier. Compression is conducted using techniques such as JPEG or GIF [24]. Feature extraction, on the other hand, involves identifying key characteristics such as edges, textures, shapes, or colors that are relevant to the analysis, typically using dedicated filters and transformations, such as the Canny detector [25] to filter an image for edges, the Gabor filter [26] to extract textures, and the Hough transformation [27] to recognize specific geometric shapes based on such filtered images [28, 29].

Finally, an analysis is performed to interpret the visual data and derive insights or classifications, depending on the application's objectives. These analyses often lead to actions in the system's operating environment, such as sorting products based on machine vision identification [30].

In recent years, machine learning approaches have gained prominence in the feature extraction and analysis stages of machine vision systems. Such models typically rely on convolutional neural networks (CNNs) or vision transformer blocks (ViT) to learn the end-to-end relation between image data as input and the desired machine vision outputs, enabling subsequent decisions and actions. Architectures such as the *You Only Look Once* (YOLO) [31] for object detection or the U-Net architecture [32] for image segmentation have already been widely used and often perform better than traditional

algorithms utilized for these machine vision tasks [33–35]. Besides such discriminative models, generative models such as *Generative Adversarial Networks* (GANs) have been introduced in recent years to enhance machine vision tasks [36]. Generative AI models are able to learn the distribution of underlying image data foundations and can use this knowledge for several downstream tasks, such as the generation of artificial data to augment training datasets for training [37].

To ensure a structured and standardized approach to integrating machine vision systems, the developed methods and processes are often formalized in norms and guidelines. An example of such a guideline is the VDI/VDE/VDMA 2632 sheet 2, which describes the general requirement engineering for machine vision integration [38]. Additional specifications and guidelines are provided for specific subtopics, including image preprocessing, acceptance tests [39, 40], and specialized areas such as surface inspections, the measurement and characterization of camera parameters [41], or visual methodological aspects in flat steel applications [42]. These guidelines not only facilitate the preparation of requirements and system specifications for machine vision systems but also ensure effective communication between suppliers and users during project phases. Furthermore, they maintain internal quality by establishing clear performance criteria and expectations.

2.2 Technology transfer in SMEs

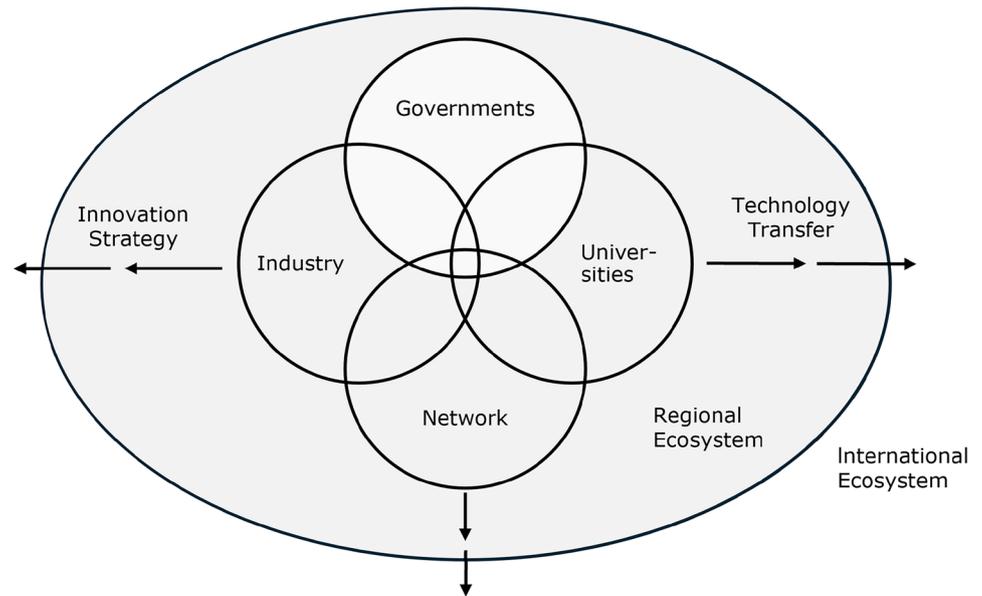
An SME is a company with employees, revenue, and assets below a certain threshold, though these thresholds vary by region. For example, in the European Union, SMEs are defined in the Commission Recommendation of 2003 as companies with fewer than 250 employees, revenue below €50 million, and a total balance sheet fewer than €43 million [43]. They are categorized with a critical role in modern economies, but fewer investment capacities compared to larger companies [9, 10, 13]. On the other hand, technology transfer describes the process of sharing or transferring technology from the person or organization that owns or holds it to another person or organization [44]. Technology transfer is vital for SMEs because it allows them to harness advanced technologies and innovations from public research, driving competitiveness and securing their future without necessarily increasing costs [45]. Thus, publicly funded institutions, acting as intermediaries, are instrumental in driving open innovation among these businesses, facilitating the adoption of new technologies [46]. For instance, the service center WestAI facilitates knowledge exchange on artificial intelligence (AI) technology in Germany, with a particular focus on industrial SMEs [47]. To better understand the broader implications of technology transfer, various conceptual frameworks have been developed. Some of these specifically focus on IT-related technology adoption in SMEs, exploring how these businesses can effectively integrate IT technologies into their operations [48]. Arenas et al. summarize technology transfer models in general within a systematic review and categorize them based on the interaction range, such as between university and industry or two industry partners [49]. Mancini et al. developed a conceptual model showing collaboration among governments, universities, and businesses facilitates SMEs' access to networks or clusters, leveraging external knowledge to boost international engagement [50]. SME-specific constraints, such as limited financial resources are described, and by integrating a multi-helix perspective, it is illustrated that collaborative networks and multi-stakeholder partnerships can foster the competencies needed for international expansion [50].

Figure 3 illustrates this model [50]. The study's findings underscore the importance of SMEs' participation in networks, enabling them to leverage external knowledge, collaborate with institutions, and improve competitiveness on a global scale. Additional frameworks exist, along with further reviews that compare them [51].

To assess the readiness of industrial SMEs in technology adoption and usage, existing literature highlights several key indicators such as the integration of industrial internet, cloud manufacturing, collaborative robots, business models, and digital transformation. These indicators are grouped into five dimensions: (1) Organizational Resilience, (2) Infrastructure System, (3) Manufacturing System, (4) Data Transformation, and (5) Digital Technology, providing a structured framework to evaluate SMEs' capabilities for integrating advanced technologies into their operations [52].

Despite this structured approach, the integration of advanced technologies presents significant challenges. Barriers such as high investment costs, unclear economic benefits, and security risks are significant hurdles that must be overcome to facilitate technology development. These barriers are particularly pronounced in the industrial domain, where organizational, technological, and environmental factors play a critical role [53]. Given this complex interplay, it becomes essential to adopt a Human-Technology-Organization (HTO) perspective, which provides a structured approach to analyzing these dynamics. The HTO (sometimes also referred to as HOT [54]) framework helps identify and address the interdependencies among human factors, technological infrastructures, and organizational structures, offering a comprehensive view of the challenges and opportunities in industrial technology adoption [55]. Building upon the foundational HTO framework, subsequent adaptations have been introduced to support the adoption of information

Fig. 3 Technology adoption model based on Mancini et al. [50]



technology in organizational technology management [56]. Table 1 summarizes the key aspects of this adapted framework. Human factors are described as individual attributes, including skills and knowledge, and interactional aspects, such as collaboration and communication. Organizational factors include internal characteristics, such as the organizational structure and IT strategy, as well as external characteristics, like industry dynamics and government regulations. Finally, technology factors encompass specific requirements, such as hardware and software, as well as broader considerations, such as information and system quality [56].

Therefore, the adoption of technology in industrial SMEs is not only a technical effort but also an organizational and human challenge. Technology transfer directly supports these dimensions by facilitating access to innovations, addressing skill gaps, and reducing financial risks [57, 58].

3 Methods

Building on the outlined fundamentals, this chapter gives an overview of the methods used in the review. It was conducted following the PRISMA methodology, which aims to ensure systematic reviews are presented transparently, comprehensively, and accurately [15]. However, only the steps relevant to our domain were implemented to ensure the approach remained tailored and applicable to the scope of the research. Firstly, we applied stringent exclusion criteria to ensure relevance and focus, to our research questions defined and listed in Table 2. Each exclusion criterion ensures the literature aligns with the specific domain of machine vision for industrial SMEs. Articles are excluded if they lack an image modality, and consequently no machine vision or image algorithm context. Similarly, papers are excluded if they do not prominently feature SMEs in either the study's motivation or its contributions. Articles that do not relate to industrial manufacturing or its surrounding research areas are also excluded. Furthermore, there are content-independent exclusion criteria. Articles not written in German or English were excluded due to language limitations. Also, articles published before 2014 are excluded to focus exclusively on current research approaches from the past decade. Further, publications that can not be accessed are excluded as their content can not be validated. Lastly, a category for exclusion based on other factors is taken into account.

We selected three databases that are particularly recognized for their suitability in engineering research: IEEEExplore, Scopus, and Web of Science. The initial search string was developed based on criteria 1, 2, and 3, and the specific terms were chosen through an internal workshop format. We used the symbol "*" to allow flexibility in word endings during the search. Three iterative cycles were conducted to refine the search string. For criteria 1, certain terms were found to be either too specific, such as "CT" for the visual procedure of computed tomography, or overly broad, like "optical*". In criteria 2, the abbreviation "SME" was challenging because it can represent various meanings (such as subject matter expert, Society of Manufacturing Engineers, set-membership estimator, or squared-mean-error). Still, it was retained due

Table 1 Human, technology, and organization factors in information technology adoption based on Xu et al

| Human factors | Technology factors | Organization factors |
|---|---|--|
| Socioeconomic characteristics: Experience | Characteristics: System quality, Information quality, Service quality | Internal characteristics: Size, Linking structures, Interaction styles and processes, Felt needs/problems |
| Interactional characteristics: Communication behavior | Requirements to Human and Organization | External characteristics: Industry characteristics and market structure, Technology support infrastructure, Government regulation |

Table 2 Exclusion criteria for selecting relevant literature

| No. | Description | Context |
|-----|-------------------------------------|--|
| 1 | No image modality context | Articles are excluded if there is no image modality, and consequently no machine vision context |
| 2 | No SME-related context | Papers are excluded if they do not prominently feature SMEs in either the study's motivation or contributions |
| 3 | No industrial manufacturing context | Articles are excluded if they lack a context related to industrial manufacturing or surrounding research areas |
| 4 | Not English or German language | Articles are excluded due to the research group's limited capacity to understand content in other languages |
| 5 | Before 2014 | Articles published before 2014 were excluded to focus on current research approaches from the past decade |
| 6 | Not accessible | Publications are excluded if not accessible with a German library license as their content cannot be validated |
| 7 | Other | Articles are excluded due to other reasons (for example conference summaries, proceedings overviews, i.a.) |

Table 3 Refined search string categories and keywords (Within each column, keywords are combined using an OR Operator; across columns, they are combined using an AND Operator, as written in Appendix 6.1

| Machine vision keywords | SMEs keywords | Industrial manufacturing keywords |
|--------------------------|---------------------------------------|-----------------------------------|
| "Computer vision" | "SME*" | "Manufactur*" |
| "Machine vision" | "Small compan*" | "Production technology" |
| "Visual inspection" | "Small business*" | "Industr*" |
| "Automated vision" | "Small-scale Industr*" | "fabricat*" |
| "Object detection" | "Micro enterprises" | "Factory" |
| "Defect detection" | "Small-scale businesses" | "IIoT" |
| "Image classification" | "Small enterprises" | "IoT" |
| "Image analysis" | "start-up" | "Production line" |
| "Semantic segmentation" | "Medium businesses" | "Assembly" |
| "Image segmentation" | "Small- and medium-sized enterprise*" | |
| "Visual quality control" | "Small- and middle-sized enterprise*" | |
| "Visual analysis" | | |
| "Optical metrology" | | |
| "Optical monitoring" | | |
| "Image synthesis" | | |
| "Image generation" | | |

An asterisk (*) indicates a wildcard to include all word variations

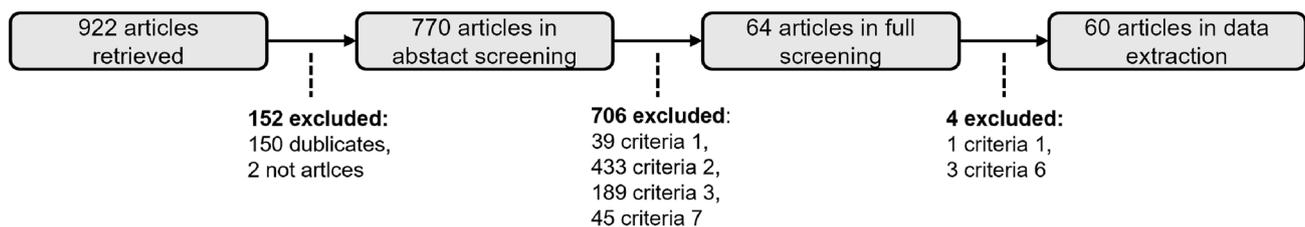


Fig. 4 Results of research selection and extraction

to its common use for small- and medium-sized enterprises. Additionally, for criteria 3, the term "industrial" was sometimes associated with medical, healthcare, or biological contexts, but it was kept because of its relevance to manufacturing contexts. Table 3 describes the final search string.

The search was conducted on July 1, 2024. Article exclusion decisions were made by two independent reviewers through an abstract screening, followed by a full-paper screening. The abstracts were randomly distributed to the reviewers. A total of 922 articles were identified in the selected search engines, with 150 duplicates and 2 additional records, that did not qualify as research articles. As a result, 770 articles were reviewed during the Abstract Screening, with 706 being excluded. This exclusion is primarily based on the usage of the abbreviation "SME" in a different context, as well as the appearance of "industry" in domains beyond the scope of this review.

This left 64 articles for full-text screening, of which 3 were excluded as they could not be accessed and 1 irrelevant regarding the exclusion criteria. The excluded articles were from fields unrelated to industrial manufacturing, did not address machine vision systems or image modality in general, or lacked relevance to organizational aspects of SMEs. Thus, 60 articles underwent data extraction. The described research selection and extraction results are illustrated in Fig. 4.

After research collection, the data extraction is done by a single reviewer process, following nine predefined questions and specific criteria. This extraction process systematically organizes key information into defined categories to address the research questions and will be done with tabular sheets. Each category is mapped to specified answer options, developed based on insights from an internal workshop conducted after extracting data from a subset of articles. An 'undefined' option is included for cases where the expected information is not provided in the article. The selected categories and option examples are listed in Table 4 as follows:

Categories 1–5 cover general information about the article. Categories 6–7 correspond to research question 1, Category 8 to research question 2, and Category 9 to research question 3. The results will be presented both quantitatively

Table 4 Data extraction categories with descriptions

| No. | Category Name | Description | Options |
|-----|----------------------|---|--|
| 1 | Title and DOI | Title and Identifier of the article | – |
| 2 | Year of Publication | Year the publication is published | 2014–2024 |
| 3 | Publication Origin | Identification of national or international origin | German, International |
| 4 | Funding | Identification of the funding type as a transfer project | Yes, No, Unclear |
| 5 | Involvement of SMEs | Direct participation of at least one SME within the publication | As author, For validation, Not directly |
| 6 | Computer Vision Task | Computer vision tasks investigated in the publications | Classification, Object Detection, Segmentation, Pose Estimation, i.a |
| 7 | Domain | Applications domain of the machine vision system proposed for the SME | Robotics, Quality Classification, Inventory Management, i.a |
| 8 | Challenges | Described challenges for SMEs | Data availability, Investment Shortage, Human Resources, i.a |
| 9 | Solution Approaches | This column captures the key results or findings of the study, highlighting the main contributions to the field | Open-source software, low-cost hardware, data augmentation, i.a |

through data visualization methods and qualitatively through summaries highlighting the most significant contributions to the research questions.

4 Results

Firstly, Sect. 4.1 describes the general properties of the identified literature based on data extraction categories 3–5 (Table 4). Then, the results are organized according to the research questions. Section 4.2 explores research question 1, focusing on the applications and general tasks of machine vision in SMEs. Section 4.3 addresses research question 2, identifying the challenges related to the development and implementation of machine vision systems in SMEs. Lastly, Section 4.4 summarizes the proposed solutions in the literature for SMEs to overcome these identified challenges.

4.1 Funding and participation of SMEs

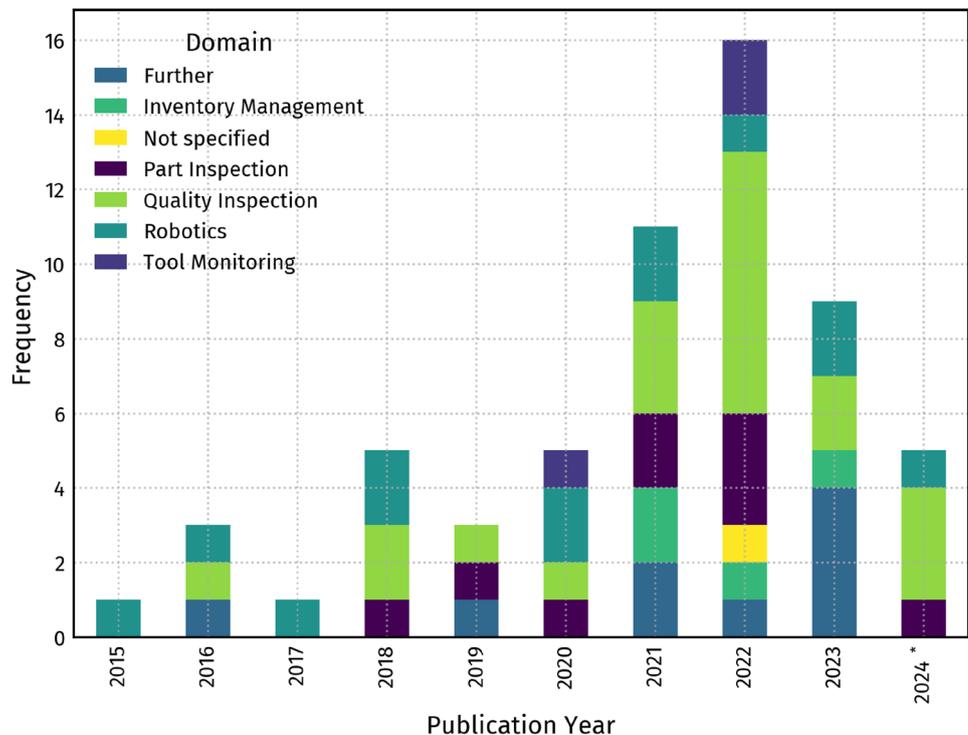
Within the identified publications, 15.9 percent are authored by German institutes or organizations, while 84.1 percent are international publications. While funding was unclear for 47.5 percent of the projects, 16.5 percent were funded through transfer projects, and 36 percent through non-transfer projects. 17.4 percent involve direct participation from SMEs, with at least one author affiliated with an SME. Additionally, 10.1 percent of the publications include SMEs in a supportive role, primarily contributing to the validation of the research. The majority, 72.5 percent, do not involve SMEs and remain purely scientific publications.

4.2 Applications and tasks of machine vision in SMEs

To answer the first of our research questions, i.e., the analysis of which tasks and in which applications SMEs use industrial machine vision, we primarily investigated the Domain and the Computer Vision Task category listed in Table 4. To address both aspects of the research question, Fig. 5 in the first place shows the distribution of the application domain of industrial machine vision in SMEs.

The literature on machine vision research for SMEs shows a notable increase in publications over the years with a peak of publications in 2022, while 2024 is included only up to July 1, as that was the search date. The increasing interest can

Fig. 5 Publication year and industrial domain frequency in the identified literature *
In 2024, articles published before July 1 are only considered



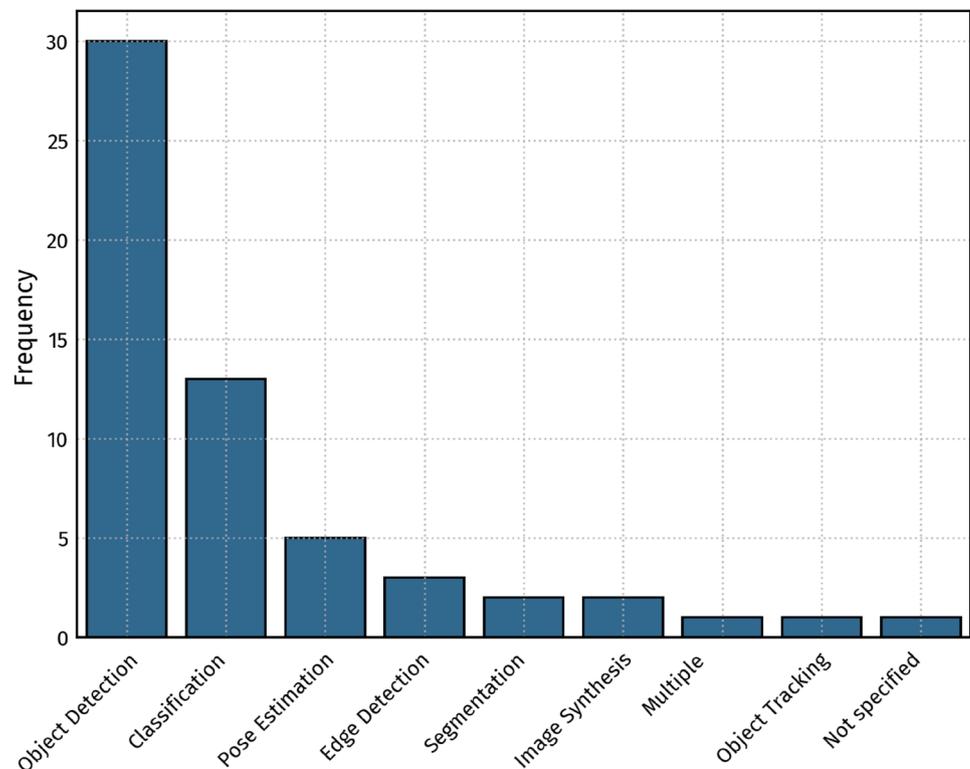
be attributed to the growing accessibility and demand for automation technology solutions to the specific needs of SMEs [59]. Nevertheless, a decline in publications in 2023 can be observed. While it is not within the scope of this review to investigate the reasons behind this decline, possible explanations include changes in funding or economic conditions, or shifting research priorities. The range of domains is increasing, showcasing the potential of machine vision across industries. While in the 2010s, machine vision is primarily utilized for robotics and quality inspection, applications in other domains, such as inventory management or tool monitoring become more relevant in the last years.

The most prominent application domain of industrial machine vision is quality inspection with about one-third of articles applying industrial machine vision to this domain. This large share might be because applications in quality inspection, in specific defect detection, have been known for a long time, and the potential of this technology has been proven in many use cases [60]. For instance, camera-based defect detection can be utilized to automate otherwise manual and monotonous work cost-efficiently while often still achieving the same level of accuracy as humans. Examples of this can be found in the articles of [61–63], and [64], in which the authors implemented defect detection for LED displays, metallic deposition processes, assembly processes, and injection molding. Besides quality inspection, a further key application domain is robotics, in which vision capabilities enhance the recognition and coordination of robotic systems, such as for autonomous movable robot arm simulations [65] or scene segmentation for robotic assembly processes [66]. Additionally, part inspection is recognized as an application area, where manufacturing components are examined using machine vision systems for dimensional accuracy, such as in the case of extruded rubber profiles [67] or for sorting purposes [68]. Smaller clusters include tool monitoring in production, for example with a focus on cost-effective solutions [69], and inventory management, such as for the mass identification of products [70].

The second aspect that is assessed concerning the research question is the computer vision tasks. As listed in Table 4, seven distinct categories were selected as being relevant. The distribution of articles over these categories is summarized in Fig. 6.

The majority of articles work on object detection tasks, followed by classification and pose estimation. Object detection can be utilized to tackle a variety of machine vision problems, such as defect detection, where defect class and location are being inferred [71], or inventory management, where an object detection task must be solved to keep track of material flows within enterprises [72]. Additionally, some machine vision tasks are being utilized in specific domains. For example, all five instances of articles focused on pose estimation are solely applied to the robotics domain. This is due to the domain-specific requirements. In robotics, actions in the open space are performed such that robots must know

Fig. 6 Frequency of computer vision tasks in the identified literature



the position of certain objects to either avoid them to prevent collisions [73] or to approach them for placing operations [11]. Besides robotics, the high number of articles working in the field of quality inspection is directly reflected by the quite high number of classification tasks tackled since almost all of the papers working on classification problems do it for quality inspection since for simple quality checks the sole information, whether a part is defective or not, is sufficient for some applications. One example can be found in the work of [74], where the authors applied such a binary classification to the quality inspection of casting parts. Both were used in the domains of quality inspection, robotics, and part inspection purposes. Furthermore, some publications handle pose estimation, edge detection tasks, segmentation, and other related tasks.

In summary, the literature highlights a growing interest in industrial machine vision for SMEs, with quality inspection and robotics as the most prominent application domains, and object detection as well as classification as the major computer vision tasks.

4.3 Challenges of machine vision development in SMEs

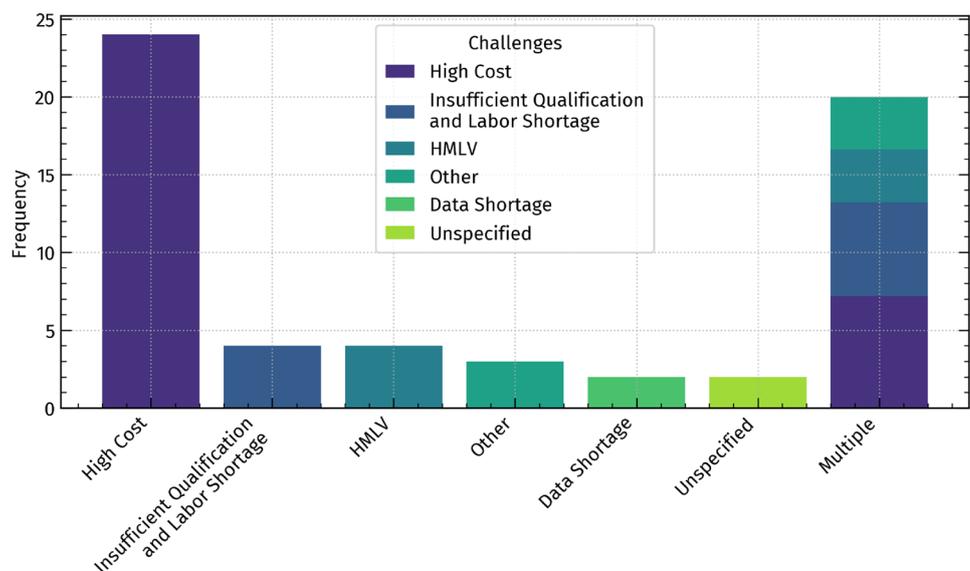
The publications highlight several challenges associated with adopting machine vision technologies. The most notable included high costs, a lack of qualified personnel or labor shortages, the complexity of High Mix and Low Volume Production (HMLV), and a shortage of data. Many of the identified articles also describe a combination of these challenges. Figure 7. illustrates these challenges, categorized into different clusters as a bar chart.

High costs arise from various factors. Traditional inspection hardware often requires substantial investment, which can be particularly challenging for SMEs and barriers in developing economies [75]. Additionally, off-premise software infrastructure entails high initial setup costs, often due to the lack of existing hardware [61], while on-premise cloud solutions are generally more expensive in the long term [70]. Besides service infrastructure, the investment required for computing power to run vision algorithms is particularly high [76]. Moreover, the generation of images along with labeling comes with high costs due to the significant time investment required from experts [77].

Articles highlight a shortage of skilled labor. General factors, such as population decline in many developed countries, particularly affect the engineering domain [62]. SMEs face a general shortage of technical staff or lack sufficient IT-trained personnel [78]. Even professional IT personnel in these companies often lack the specialized skills needed to adopt new cutting-edge technologies [79]. Additionally, organizational aspects, such as employee acceptance, hinder small organizations without clear processes [8]. Overall, skills shortages are significantly more likely to affect manufacturing SMEs than large enterprises [80].

Furthermore, managing HMLV is challenging because it requires the production of a diverse range of products, each in limited quantities. The current trends are pushing the manufacturing sector towards HMLV, which calls for collaborative and more flexible solutions and production systems [81]. In SMEs, it is even more, as few-of-a-kind production is more typically due to less automation [82]. Since the production volume for each product is limited, labeled data are scarce [83].

Fig. 7 Identified challenges for industrial SMEs in machine vision adoption (The bar labeled “Multiple” shows the distribution of overlapping challenges in relative proportions)



This presents challenges in adapting algorithms to accommodate a wide variety of shapes, sizes, and features, without requiring too much data for training with each product. Data availability itself is another challenge. SMEs often face a lack of accessible datasets, particularly labeled ones [84]. Even when data is available, it is frequently unbalanced due to the rarity of defective products in their processes [64].

The 'Multiple' bar reflects cases where multiple challenges overlap, with segments representing each challenge proportionally according to their frequency. Among the 20 articles addressing multiple grouped challenges, 9 highlighted HMLV and 14 highlighted Insufficient Qualification and Labor Shortage, though both appear less prominently in the bar chart compared to High costs.

Some articles also mention other barriers, such as the low workload of individual applications, which makes automation less feasible [65], as well as the challenges posed by tedious manual assembly [71]. Furthermore, the lack of proper equipment, often linked to investment restrictions, poses a significant barrier [73]. Even when use cases exist, there is often insufficient workload in a single specific context, making automation more challenging [85]. Furthermore, human-related aspects, such as mistrust in machine vision technology and employee acceptance, have been highlighted [8, 14]. A categorization of these challenges in the context of HTO can be achieved by describing each aspect based on Table 5, highlighting the critical focus on technology aspects along with human and organizational aspects. Table 5 presents all articles, their categorization as HTO, and the corresponding challenge category [56]. The categorization process was conducted independently by two researchers. Afterward, contradictions were resolved collaboratively to select the final categorization.

Although many challenges have been identified, the main challenges for adopting machine vision technology in SMEs presented are high cost, insufficient qualification and labor shortage, HMLV and data shortage, and their combinations. These challenges include human technological and organizational aspects with a particular emphasis on technological requirements.

4.4 Approaches and solutions for machine vision adoption SMEs

The articles present different approaches for integrating machine vision in industrial SMEs. Firstly, the selection of low-cost hardware components, such as Arduino-based vision control [69] or single-board computers like Raspberry Pi [99]. Hardware components were often tailored to domain-specific requirements, such as flying tracking systems for data collection along the entire production environment [95]. Additionally, open-source software such as OpenCV [82], combined with tailored software specifications, including various combinations of software modules [105], was presented. Some of these also work out-of-the-box as pre-trained models [91]. Other approaches were designed to be used intuitively by user. Further data augmentation techniques, such as those that generate data using algorithms [64], including GANs or synthetic computer-aided design (CAD)-based approaches [115]. Figure 8 clusters these approaches based on the challenges described in the corresponding research.

Numerous approaches have been explored to address high-cost challenges, with many articles emphasizing the adoption of open-source software [8, 69]. It offers the dual benefits of cost-free usage and modular expandability, allowing customization to suit specific machine vision use cases. Such tailored software has also been presented, along with out-of-the-box solutions that reduce the monetary investment typically required for system integration [109]. Additionally, low-cost hardware components were presented, offering sufficient attributes to address the use case under consideration with less monetary investment required [72]. These hardware components included sensors, such as cameras and lenses, or robots equipped with visual applications [11, 103].

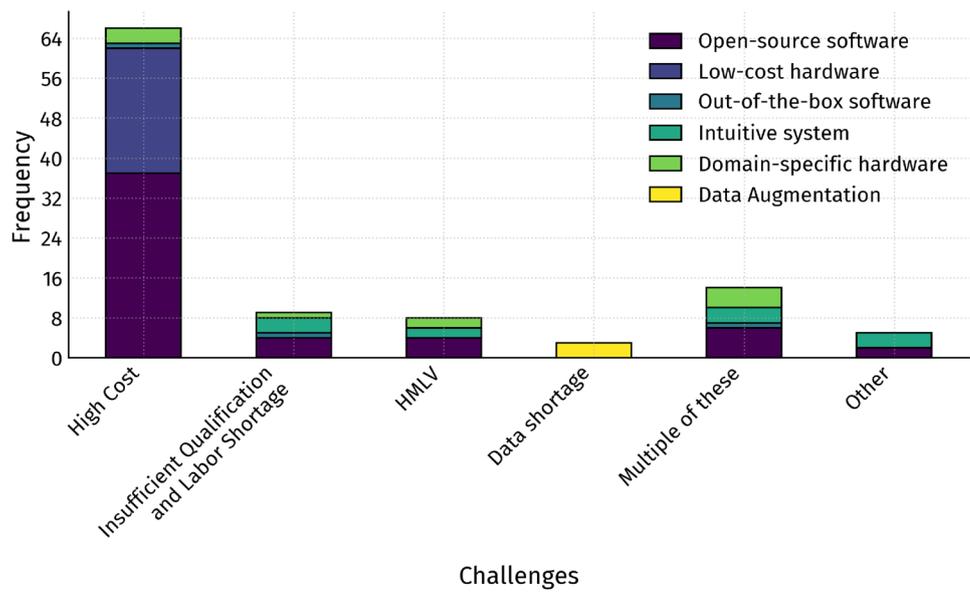
Insufficient qualification and labor shortages are also addressed through intuitive systems. The articles introduced user-friendly systems designed to facilitate intuitive interaction with users [84, 110]. Also, research proposes an augmented reality approach for intuitive programming in robotic vision systems [102]. Further out-of-the-box solutions, such as the automatic generation of digital twins are presented, which also cover vision applications [109].

HMLV is addressed through different approaches. Learning-based vision systems are introduced with adaptations to varying conditions [110]. Additionally, easily reconfigurable systems are proposed, allowing for seamless adaptation to new situations [82]. Data shortage was further addressed using data augmentation techniques. Various approaches were proposed, including commonly known methods such as rotations and flips of existing visual image data [64] or modifications to lighting conditions [84]. Further research proposes generating fully synthetic data based on CAD data, which are often available in manufacturing environments [115]. Additionally, transfer learning was proposed as an effective approach to address data scarcity. This method involves leveraging pre-trained conventional models and fine-tuning them using only a limited amount of new data specific to the target application [8].

Table 5 Papers identified for machine vision challenges in SMEs

| Challenge | HTO | References |
|---|--|---|
| High Cost | O: Organisational Challenge (IT Strategy and organisation size), T: Technological Challenge (hardware and software) | Zhou et al. [75], Sahay et al. [86], Souza et al. [11], Yadav et al. [68], Block et al. [77], Ullah et al. [87], Vaher et al. [88], Ahmed et al. [89], Horputra et al. [90], Vukicevic et al. [67], Brezani et al. [91], Park et al. [76], Kubik et al. [92], Besisle et al. [93], Im et al. [94], Gunal [95], Singh et al. [84], Voutsinas et al. [96], Safari et al. [12], Ahmed et al. [89], Lin et al. [70], Saad et al. [97], Vikram et al. [98], Ardhya et al. [99], Rahman et al. [100], Bian et al. [101] |
| | H: Human Challenge (skills and knowledge), T: Technological Challenge (information and system quality) | Polonara et al. [79], Wassermann et al. [102], Brezani et al. [91], Park et al. [62] |
| Insufficient Qualification and Labor Shortage | O: Organisational Challenge (industry characteristics), T: Technological Challenge (software required) | Ivanovska et al. [82], Bevec et al. [103], Denisa et al. [81], Simeth et al. [83], Zhang et al. [104] |
| | T: Technological Challenge (data required, software required) | Ha et al. [64], Singh et al. [84] |
| Data Shortage | HTO (Combination of the four described challenges) | Zhou et al. [78], Anas et al. [105], Eissa et al. [106], Takashi et al. [107], Li et al. [85], Princz et al. [13], Werheid et al. [8], Kim et al. [74], Beibei et al. [108], Sommer et al. [109], Xing et al. [69], Yang et al. [110], Zhang et al. [104], Hong et al. [111], Shaloo et al. [63], Wang et al. [112], Soundattikar et al. [113], Christiansen et al. [14], Yang et al. [110] |
| Multiple of These | HTO (Combination of the four described challenges) | Ahmad et al. [73], Mukhopadhyay et al. [71], Vaher et al. [65] |
| Other | Not categorized | Wiedholz et al. [66], Bu et al. [114] |
| Unspecified | Not categorized | |

Fig. 8 Solution approaches in reviewed literature categorized along with their corresponding challenges



Within the review literature, SMEs are frequently presented as the initial motivation for the research. Yet, the core focus often shifts to highly specific problems that are not broadly applicable to the common challenges SMEs face. Twenty articles were identified within the review as offering the most interesting integrative approaches for machine vision development within SMEs addressing the challenges presented. These articles, summarized in Table 6, are classified as contributions in the categories HTO aspects.

The reviewed research proposes a variety of approaches based on hardware and software considerations. Some studies explore human aspects within human-technology interaction [106, 108], while others identify organizational barriers faced by SMEs [13, 81]. The majority of the research, however, focuses on proposing technical concepts tailored to application domains, addressing the specific challenges encountered by SMEs. No comprehensive framework has been identified for the integration of machine vision technology in industrial SMEs that addresses the various challenges or combines the proposed solution approaches into a holistic methodology.

5 Discussion and outlook

Machine vision systems are widely used in various industrial manufacturing sectors and cover key automation in quality control, inventory management, part inspection, and further processes. Despite ongoing adoption, SMEs face unique challenges in integrating these technologies due to various technological and organizational constraints. Although many research articles contribute to the development of machine vision for industrial SMEs, no comprehensive literature review identifies the intersection and differences among these contributions. This article presented a systematic review, based on the PRISMA guidelines, to address three research questions related to current research in machine vision development for SMEs. By analyzing 770 articles, this review offers insights into the characteristics of machine vision systems in industrial SMEs, their challenges, and proposed solutions. The results revealed increased publications over the years, with German participation accounting for 15.9 percent of all articles, reflecting Germany's interest in SME development (noting that 3 of the 64 identified articles were inaccessible due to library license constraints, which could introduce minor bias). The prominent applications were quality control and robotics with the majority of these dealing with object detection tasks, followed by classification and pose estimation. Although many challenges have been described, the main challenges identified were high cost, insufficient qualification, and labor shortage, HMLV and data shortage, and their combinations. These included human technological and organizational aspects with a focus on technology. Various software and hardware approaches were presented to address the investigated challenges. Key contributions included several architectures for low-cost vision systems, such as the selection of Arduino or Raspberry PI for image processing to handle high costs [69, 99]. Additionally, systems that are easy to integrate and control, such as those using human instructions for robot programming, were proposed [108]. Vision algorithms designed to handle data shortages and the high variety of detection objects, due to HMLV, were introduced using synthetic data and transfer learning [8, 115].

Table 6 Overview of most relevant papers discussing solutions for machine vision integration in industrial SMEs

| Title and Authors | Type of Paper (HTO) | Descriptions |
|---|---|---|
| Learning-based object detection and localization for a mobile robot manipulator in SME production Zhou et al. [78] | Technical Contribution | This article describes an object detection solution based on deep learning on 3D point clouds for a collaborative mobile robot manipulator to automate SME production. The focus is on enhancing detection robustness in dynamic SME working environments through deep learning algorithms that address uncertainties in object detection within point cloud |
| An effective programming by demonstration method for SMEs' industrial robots Eissa et al. [106] | Human and Technical Contribution | The approach includes the development of a cost-effective and robust Programming by Demonstration method for industrial robots. The user can demonstrate the robotic movement with a 5-spherical passive marker, that is tracked by a vision system. The article focuses on reducing programming time and complexity for SMEs while ensuring a sufficient level of accuracy |
| Affordable Artificial Intelligence-Assisted Machine Supervision System for the Small and Medium-Sized Manufacturers Li et al. [85] | Technical Contribution | The authors propose an affordable AI-assisted machine supervision system for SMEs in the manufacturing sector, utilizing computer vision to enhance monitoring, optimize productivity, and reduce costs. The system is designed to be cost-efficient, using open-source software for object detection and low-cost hardware featuring a webcam and an embedded chip |
| A literature review on the prediction and monitoring of assembly and disassembly processes in discrete make-To-order production in SMEs with machine vision technologies Prinz et al. [13] | Technical and Organizational Contribution | This article provides a comprehensive literature review on the application of machine vision technologies for predicting and monitoring assembly and disassembly processes in SMEs. Although many technical and organizational approaches have been identified, the authors describe a lack of holistic solutions for SMEs |
| Demonstrating computer vision to small- and medium-sized enterprises in manufacturing: Toward overcoming costs and implementation challenges Werheid et al. [8] | Technical Contribution | The authors propose a cost-effective portable computer vision system to demonstrate the feasibility and applicability of computer vision for SMEs in manufacturing on industrial fairs. They use open-source classification algorithms and a low-cost camera connected to a Raspberry Pi |
| Image-Bot: Generating Synthetic Object Detection Datasets for Small and Medium-Sized Manufacturing Companies Block et al. [77] | Technical Contribution | As SMEs often work with highly specialized objects, making the use of publicly available or commercial training datasets difficult, the authors propose a method for synthetic data generation. The 'Image-Bot' is a solution designed to generate synthetic object detection datasets by masking objects and automatically placing them into images, thereby effectively generating multiple images for object detection |
| Architecture for task-dependent human-robot collaboration Beibel et al. [108] | Human and Technical Contribution | The authors propose an architecture for task-dependent human-robot collaboration aimed at enhancing flexibility and agility in manufacturing, specifically targeting SMEs, to handle the complexity of robot programming. The system is designed to automatically detect an object presented by a human and compare it to a library of potential tasks, each of which triggers a corresponding robot movement |

Table 6 (continued)

| Title and Authors | Type of Paper (HTO) | Descriptions |
|---|---|---|
| Automated generation of digital twin for a built environment using scan and object detection as input for production planning Sommer et al. [109] | Technical Contribution | This article describes a method for automatically generating digital twins of production environments by leveraging scans and object detection, to simplify the process for SMEs |
| Low-Cost Precision Monitoring System of Machine Tools for SMEs Xing et al. [69] | Technical Contribution | The paper discusses the development of a machine tool data acquisition process that utilizes a precision monitoring system built on low-cost ESP32 hardware and open-source platforms. This system is specifically designed for SMEs because of its simple setup and low total cost, while also demonstrating how it can be integrated into existing cloud infrastructures |
| Technology Modules Providing Solutions for Agile Manufacturing Denisa et al. [81] | Technical and Organizational Contribution | This paper presents an overview of methodologies and evaluations of 14 innovative solutions, including vision systems, providing comprehensive and multifaceted summaries to address the evolving needs and demands of the manufacturing sector, especially for SMEs. The presented methodologies are designed to be both cost-effective and modular, making them suitable for integration into existing systems or stand-alone applications |
| Hand-Monitoring System Using CutMix-Based Synthetic Augmentation for Safety in Factories Park et al. [76] | Technical Contribution | This paper presents a cost-effective safety monitoring system for SMEs that leverages synthetic data to overcome data acquisition challenges. The synthetic data is generated using a CutMix-based approach, which involves cutting segments from images and combining them to create new ones, and it was later validated on-site at an industrial SME |
| Smart extensions to regular cameras in the industrial environment Brezani et al. [91] | Technical Contribution | This paper presents smart extensions to regular cameras, proposing a fast emergency aid system for industrial environments. The system is designed under the assumption that SMEs have few IT personnel and operate without any additional data to detect safety-critical situations in SME production with pre-trained object detection models |
| IoT-enabled computer vision-based parts inspection system for SME 4.0 Ullah et al. [87] | Technical Contribution | The authors propose a low-cost, modular computer vision-based measurement (CVIM) system with IoT integration for inspecting three-dimensional mechanical parts, enhancing efficiency and accuracy. By focusing on low-cost components and modular design, it specifically mentions and addresses the production needs of SMEs |
| A smart warehouse 4.0 approach for the pallet management using machine vision and Internet of things (IoT): A real industrial case study Vukicevic et al. [72] | Technical Contribution | This article presents a cost-effective and smart Warehouse 4.0 solution for SMEs in the printing industry. The authors focus on cost efficiency by integrating QR codes, surveillance equipment, and open-source machine vision tools to improve pallet tracking. They also address specific challenges in smart warehousing for SMEs, such as effectively managing inventory of available parts in environments with less standardized practices, like inconsistent application of first-in, first-out rules |

Table 6 (continued)

| Title and Authors | Type of Paper (HTO) | Descriptions |
|---|--|--|
| Decision Support System for Dimensional Inspection of Extruded Rubber Profiles Yukicevic et al. [67] | Technical Contribution | The paper describes a computer vision-based solution for SMEs in the automotive industry to automate rubber profile inspection, improving quality assurance processes. It is specifically designed for SMEs by utilizing low-cost hardware and software and ensuring that the application operates as a stand-alone system with direct output, even in production environments that are not fully digitalized |
| Automation of SME production with a Cobot system powered by learning-based vision Yang et al. [110] | Technical Contribution | This article presents a framework to automate production in SMEs using collaborative robots equipped with learning-based vision systems for object detection and quality control. The framework integrates various algorithms for robotic control and training within a digital twin platform, enabling easy deployment, troubleshooting, and customization. Furthermore, it has been tested with an industrial partner to demonstrate its accuracy and efficiency in automating production processes, offering a scalable solution for broader SME applications |
| Machine learning-based real-time monitoring system for smart connected worker to improve energy efficiency Bian et al. [101] | Technical Contribution | The authors propose a system for real-time monitoring of manufacturing workflows, improving energy efficiency. By incorporating low-cost components and open-source software, it addresses the needs of SMEs. Moreover, existing communication protocols are employed to provide SMEs flexibility during the integration process |
| Comparative assessment of common pre-trained CNNs for vision-based surface defect detection of machined components Singh et al. [84] | Technical Contribution | This article provides a detailed evaluation of pre-trained CNNs for machine vision applications in SMEs, focusing on the detection of surface defects on machined components. Due to data availability challenges faced by many SMEs, the article investigates training on publicly available datasets and employs domain-specific data for further fine-tuning of the models |
| Identification of Barriers to and Opportunities for Adoption of Machine Vision for Small and Medium-sized Enterprises Christiansen et al. [14] | Human, Technical and Organizational Contribution | The paper investigates the challenges and potential opportunities for SMEs in adopting machine vision technologies within the Industry 4.0 framework, highlighting key barriers and opportunities through interviews. While the rapid pace of technological development and decreasing costs offer significant opportunities, many challenges remain, such as robustness issues, mistrust in AI, and a lack of competencies |
| Flexible and robust detection for assembly automation with YOLOv5: a case study on HMLV manufacturing line Simeth et al. [83] | Technical Contribution | This article investigates the application of the YOLOv5 object detection algorithm in automating assembly tasks within HMLV production lines in SMEs, demonstrating its potential to improve flexibility and automation. The authors examined the effects of varying product flexibilities, lighting, and background conditions, and found that current YOLO models require only minimal additional training data when conditions change |

The review revealed a lack of conceptual models for machine vision integration in industrial SMEs that address various HTO challenges. In articles referencing funding, approximately one-third were supported by transfer research, highlighting their contribution to this field. Additionally, while the results were robust, they primarily reflect a research perspective, with limited direct involvement from SMEs, which may affect the practical applicability of some findings. This can be concluded from the fact that only 17.4 percent of the reviewed articles feature direct SME participation, 10.1 percent involve SMEs in a supportive role, and 72.5 percent do not involve SMEs. Despite the frequent use of transfer projects and public funding, SME engagement in research remains limited. To ensure practical applicability, future funding calls, and transfer initiatives should explicitly encourage SME participation, thereby strengthening the link between research and industry needs.

The search strategy used in this review is defined by the specific research string employed. Future studies may broaden and refine this search string, to identify more research articles and expand the generalizability of the results. For example, relaxing the keywords related to small and medium-sized enterprises could increase the search and thus, add additional value to the answer to the research questions. Besides, future research that focuses on the perspective of SMEs, utilizing questionnaire approaches or even interview formats, could build upon the research questions investigated in this article to gain insights from a more applied and practical perspective of industrial SMEs. Further, a conceptual framework describing the integration process along the identified characteristics, challenges, and modular solution approaches could provide holistic guidance for industrial SMEs in adopting machine vision technology. Such a framework could help bridge the gap between theoretical insights and practical challenges by aligning industry-specific requirements with proposed solutions in a scalable and adaptable way. Structured around key integration phases such as requirements analysis, hardware selection, software implementation, and system operation, it could offer a step-by-step approach tailored to the needs and constraints of SMEs.

Author contributions Jonas Werheid: Conceptualization, Literature Search, Data Analysis, Writing. Hannes Behnen: Literature Search, Data Analysis, Writing. Jan-Henrik Woltersmann: Literature Search, Data Analysis, Writing. Shengjie He: Literature Search, Data Analysis, Writing. Tobias Hamann: Writing — Review. Anas Abdelrazeq: Writing — Review. Robert H. Schmitt: Writing — Review, Supervision, Funding acquisition.

Funding Open Access funding enabled and organized by Projekt DEAL. The authors thank the German Federal Ministry of Education and Research (BMBF) for the WestAI project (Grant no. 01IS22094D), conducted within the AI Service Centers framework. Further, the Federal Ministry of Labour and Social Affairs (BMBS) and the European Union through the European Social Fund Plus (ESF Plus) for the project ZUKIPRO as part of the “Future Centers”.

Data availability No data is associated with or published as part of this research.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors have no Conflict of interest to declare that are relevant to the content of this article.

Appendix

Full search string

("computer vision" OR "machine vision" OR "visual inspection" OR "automated vision" OR "object detection" OR "defect detection" OR "image classification" OR "image analysis" OR "semantic segmentation" OR "image segmentation" OR "visual quality control" OR "visual analysis" OR "optical metrology" OR "optical monitoring" OR "image synthesis" OR "image generation") AND ("SME*" OR "Small compan*" OR "Small business*" OR "Small-scale Industr*" OR "Micro enterprises" OR "Small-scale businesses" OR "Small enterprises" OR "start-up" OR "Medium businesses" OR "Small- and medium-sized

enterprise*" OR "Small- and middle-sized enterprise*") AND ("manufactur*" OR "production technology" OR "Industr*" OR "fabricat*" OR "factory" OR "IoT" OR "IoT" OR "production line" OR "Assembly")

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Rüßmann M, Lorenz M, Sousa Gerbert P, Waldner M, Justus J, Engel P, Harnisch MJ. Industry 4.0: The future of productivity and growth in manufacturing industries April 09. 2016. <https://api.semanticscholar.org/CorpusID:140076682>.
2. Akundi A, Reyna M. A machine vision based automated quality control system for product dimensional analysis. *Procedia Comput Sci*. 2021;185:127–34. <https://doi.org/10.1016/j.procs.2021.05.014>.
3. Chauhan V, Surgenor B. A comparative study of machine vision based methods for fault detection in an automated assembly machine. *Procedia Manuf*. 2015;1:416–28. <https://doi.org/10.1016/j.promfg.2015.09.051>.
4. Joshi KD, Surgenor BW. Small parts classification with flexible machine vision and a hybrid classifier. In: 2018 25th International Conference on Mechatronics and Machine Vision in Practice (M2VIP), 2018;1–6. <https://doi.org/10.1109/M2VIP.2018.8600819>.
5. Villegas-Ch W, Navarro AM, Sanchez-Viteri S. Optimization of inventory management through computer vision and machine learning technologies. *Intell Syst Appl*. 2024;24: 200438. <https://doi.org/10.1016/j.iswa.2024.200438>.
6. Fortune Business Insights: Computer Vision Market. [Online]. Available: <https://www.fortunebusinessinsights.com/computer-vision-market-108827>. [Accessed: Aug. 28, 2024] 2024.
7. Statista. Computer Vision - Worldwide | Market Size. Accessed: 2024-11-10 (2024). <https://www.statista.com/outlook/tmo/artificial-intelligence/computer-vision/worldwide#market-size>.
8. Werheid J, Münker S, Klasen N, Hamann T, Abdelrazeq A, Schmitt RH. Demonstrating computer vision to small- and medium-sized enterprises in manufacturing: toward overcoming costs and implementation challenges. *Eng Reports*. 2024;6(11):12910. <https://doi.org/10.1002/eng2.12910>.
9. Statista. Anteil der KMU in Deutschland an allen Unternehmen nach Wirtschaftszweigen. [Online]. Available: <https://de.statista.com/statistik/daten/studie/731918/umfrage/anteil-der-kmu-in-deutschland-an-allen-unternehmen-nach-wirtschaftszweigen/#~:text=Die> [Accessed: Aug. 28, 2024] 2024.
10. Weston B. How small manufacturing businesses drive the U.S. economy 2024. Accessed: 2024-11-30.
11. Souza JPC, Rocha LF, Filipe VM, Boaventura-Cunha J, Moreira AP. Low-cost and reduced-size 3d-cameras metrological evaluation applied to industrial robotic welding operations. In: 2021 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), 2021;123–129. <https://doi.org/10.1109/ICARSC52212.2021.9429788>.
12. Safari P, Shariati B, Przewozny D, Chojeci P, Fischer JK, Freund R, Vick A, Chemnitz M. Edge cloud based visual inspection for automatic quality assurance in production. In: 2022 13th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP), 2022;473–476. <https://doi.org/10.1109/CSNDSP54353.2022.9907957>.
13. Princz G, Shaloo M, Erol S. A literature review on the prediction and monitoring of assembly and disassembly processes in discrete make-to-order production in smes with machine vision technologies. In: Proceedings of the 2023 10th International Conference on Industrial Engineering and Applications. ICIEAEU '23, pp. 318–327. Association for Computing Machinery, New York, NY, USA 2023. <https://doi.org/10.1145/3587889.3588217>.
14. Christiansen L, Antonen M, Basar M, Nannerup P. Identification of barriers to and opportunities for adoption of machine vision for small and medium-sized enterprises. 2022. <https://doi.org/10.1109/ETFA52439.2022.9921607>.
15. ...Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW, Mayo-Wilson E, McDonald S, McGuinness LA, Stewart LA, Thomas J, Tricco AC, Welch VA, Whiting P, Moher D. The PRISMA statement: an updated guideline for reporting systematic reviews. *BMJ*. 2020;2021:372. <https://doi.org/10.1136/bmj.n71>.
16. Konstantinidis F, Mouroutsos S, Gasteratos A. The role of machine vision in industry 4.0: an automotive manufacturing perspective, 2021;1–6. <https://doi.org/10.1109/IST50367.2021.9651453>.
17. Huang C-Y, Hong J-H, Huang E. Developing a machine vision inspection system for electronics failure analysis. *IEEE Trans Components Packaging Manuf Technol*. 2019;9(9):1912–25. <https://doi.org/10.1109/TCPMT.2019.2924482>.
18. Deng L, Liu G, Zhang Y. A review of machine vision applications in aerospace manufacturing quality inspection. In: 2024 4th International Conference on Computer, Control and Robotics (ICCCR), 2024;31–39. <https://doi.org/10.1109/ICCCR61138.2024.10585378>.
19. Kadam P, Fang G, Zou JJ. Object tracking using computer vision: a review. *Computers*. 2024. <https://doi.org/10.3390/computers13060136>.
20. Beyerer J, Puente León F, Frese C. *Machine Vision: Automated Visual Inspection: Theory, Practice and Applications*. Springer, 2016. <https://doi.org/10.1007/978-3-662-47794-6>.
21. Golnabi H, Asadpour A. Design and application of industrial machine vision systems. *Robot Comput-Integr Manuf*. 2007;23(6):630–7. <https://doi.org/10.1016/j.rcim.2007.02.005>.

22. Wiley V, Lucas T. Computer vision and image processing: a paper review. *Int J Artif Intell Res.* 2018;2:22. <https://doi.org/10.29099/ijair.v2i1.42>.
23. Zhou W, Ma X, Zhang Y. Research on image preprocessing algorithm and deep learning of iris recognition. *J Phys Conf Ser.* 2020;1621:012008. <https://doi.org/10.1088/1742-6596/1621/1/012008>.
24. Parmar C. A review of image compression.
25. Canny J. A computational approach to edge detection. *Pattern Analysis and Machine Intelligence, IEEE Transactions on.* 1986;PAMI-8:679–98. <https://doi.org/10.1109/TPAMI.1986.4767851>.
26. Gabor D. Theory of communication. *J Inst Electric Eng Part I General.* 1946;94:58–58.
27. Hough PVC. Method and means for recognizing complex patterns 1962.
28. Zhong Y, Jain AK. Object localization using color, texture and shape. *Pattern Recogn.* 2000;33(4):671–84. [https://doi.org/10.1016/S0031-3203\(99\)00079-5](https://doi.org/10.1016/S0031-3203(99)00079-5).
29. Wang J, Xu Z, Liu Y. Texture-based segmentation for extracting image shape features. 2013 19th International Conference on Automation and Computing, 2013;1–6.
30. Liu L-y, Luo M, Wu Y-m. Application of machine vision on the nut collars sort system. In: *Proceedings of the 2015 International Industrial Informatics and Computer Engineering Conference*, pp. 797–801. Atlantis Press, 2015/03. <https://doi.org/10.2991/iiicec-15.2015.179>.
31. Redmon J, Divvala S, Girshick R, Farhadi A. You Only Look Once: Unified, Real-Time Object Detection 2016. [arXiv:1506.02640](https://arxiv.org/abs/1506.02640).
32. Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation 2015. [arXiv:1505.04597](https://arxiv.org/abs/1505.04597).
33. Valizadeh M, Wolff SJ. Convolutional neural network applications in additive manufacturing: a review. *Adv Ind Manuf Eng.* 2022;4: 100072. <https://doi.org/10.1016/j.aime.2022.100072>.
34. Vu TTH, Pham D-L, Chang T-W. A yolo-based real-time packaging defect detection system. *Procedia Comput Sci.* 2023;217:886–94. <https://doi.org/10.1016/j.procs.2022.12.285>.
35. O'Mahony N, Campbell S, Carvalho A, Harapanahalli S, Hernandez GV, Krpalkova L, Riordan D, Walsh J. Deep learning vs. traditional computer vision. In: Arai, K, Kapoor, S. (eds.) *Advances in Computer Vision, 2020*;128–144. Springer, Cham.
36. Zhou HA, Wolfschläger D, Florides C, Werheid J, Behnen H, Woltersmann J-H, Pinto TC, Kemmerling M, Abdelrazeq A, Schmitt RH. Generative AI in Industrial Machine Vision—a review 2024. [arXiv:2408.10775](https://arxiv.org/abs/2408.10775)
37. Abou Akar C, Massih R, Yaghi A, Khalil J, Kamradt M, Makhoul A. Generative adversarial network applications in industry 4.0: a review. *Int J Comput Vision.* 2024;132:1–60. <https://doi.org/10.1007/s11263-023-01966-9>.
38. VDI/VDE/VDMA: VDI/VDE/VDMA 2632 Blatt 2:2015-10, Machine vision - Guideline for the preparation of a requirement specification and a system specification. Standard document 2015.
39. VDI/VDE/VDMA: VDI/VDE/VDMA 2632 Blatt 3:2017-10, Machine vision/industrial image processing - Acceptance test of classifying machine vision systems. Standard document 2017.
40. VDI/VDE/VDMA. VDI/VDE/VDMA 2632 Blatt 3.1:2020-08, Machine vision/industrial image processing - Acceptance test of classifying machine vision systems - Test of classification performance. Standard document 2020.
41. EMVA. EMVA 1288 Standard: This standard focuses on the characterization and measurement of camera parameters, providing a common framework for evaluating and comparing different machine vision systems. Standard document.
42. VDI/VDE/VDMA. VDI/VDE/VDMA 2632 Blatt 4.1:2020-08, Machine vision/industrial image processing - Surface inspection systems in flat steel production - Stability testing. Standard document. 2020.
43. European Commission. Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises. *Official Journal of the European Union*, L 124, 20 May 2003, 2003;36-41. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32003H0361> Accessed 2024-12-04.
44. Bozeman B. Technology transfer and public policy: a review of research and theory. *Res Policy.* 2000;29(4):627–55. [https://doi.org/10.1016/S0048-7333\(99\)00093-1](https://doi.org/10.1016/S0048-7333(99)00093-1).
45. Fechtelpeter C, Kühn A, Dumitrescu R, Ebbesmeyer P. Integrated technology transfer concept for fostering innovation in smes. In: Hörlesberger, M, Hribernik, B.E. (eds.) *Proceedings of the 26th International Association for Management of Technology Conference*, 14. - 18. Mai 2017, IAMOT 2017.
46. Battistella C, Ferraro G, Pessot E. Technology transfer services impacts on open innovation capabilities of smes. *Technol Forecasting Soc Change.* 2023;196: 122875. <https://doi.org/10.1016/j.techfore.2023.122875>.
47. WestAI: KI-Beratung & Entwicklung. Zugriff am 10. November 2024 (2024). <https://westai.de/services/beratung-und-entwicklung/>.
48. Nguyen T. Information technology adoption in smes: an integrated framework. *Int J Entrepreneurial Behav Res.* 2009;15:162–86. <https://doi.org/10.1108/13552550910944566>.
49. Arenas JJ, González D. Technology transfer models and elements in the university-industry collaboration. *Adm Sci.* 2018;8:19. <https://doi.org/10.3390/admsci8020019>.
50. Mancini S, González J. Role of technology transfer, innovation strategy and network: a conceptual model of innovation network to facilitate the internationalization process of smes. *Technol Investment.* 2021;12:82–128. <https://doi.org/10.4236/ti.2021.122006>.
51. Farhadikhah Z, Dibaj SH. A review of methods and models of technology transfer. *Int Lett Soc Hum Sci.* 2015;62:173–81. <https://doi.org/10.18052/www.scipress.com/ILSHS.62.173>.
52. Chonsawat N, Sopadang A. Defining smes' 4.0 readiness indicators. *Appl Sci.* 2020. <https://doi.org/10.3390/app10248998>.
53. Müller J, Islam N, Kazantsev N, Romanello R, Olivera G, Das D, Hamzeh R. Barriers and enablers for industry 4.0 in smes: a combined integration framework. *IEEE Trans Eng Manag.* 2024. <https://doi.org/10.1109/TEM.2024.3365771>.
54. Erlirianto LM, Ali AHN, Herdiyanti A. The implementation of the human, organization, and technology-fit (hot-fit) framework to evaluate the electronic medical record (emr) system in a hospital. *Procedia Comput Sci.* 2015;72:580–7. <https://doi.org/10.1016/j.procs.2015.12.166>.
55. Karlun J, Karlun A, Berglund M. Activity — the core of human-technology-organization. In: Black, N.L, Neumann, W.P, Noy, I. (eds.) *Proceedings of the 21st Congress of the International Ergonomics Association (IEA 2021)*, 2021;704–711. Springer, Cham.
56. Xu J, Lu W. Developing a human-organization-technology fit model for information technology adoption in organizations. *Technol Soc.* 2022;70: 102010. <https://doi.org/10.1016/j.techsoc.2022.102010>.

57. Forouhar M, Forouhar M, Gholami S, Arghish O. Identify and rank the barriers to technology transfer—analytic hierarchy process. *Math Models Methods Appl Sci*. 2016;10:142. <https://doi.org/10.5539/MAS.V10N9P142>.
58. Jones MK, Jain R. Technology transfer for smes: challenges and barriers. *Int J Technol Transfer Commercialisation*. 2002;1:146–62. <https://doi.org/10.1504/IJTTC.2002.001781>.
59. Priyashan WDM, Thilakarathne NN. Iot framework for sme level injection molding industry in the context of industry 4.0. *SSRN Electronic J*. 2020. <https://doi.org/10.2139/ssrn.3750588>.
60. Reyna M, Delgado G, Akundi A, Luna S, Chumacero E. Product digital quality inspection using machine vision systems — a categorical review. In: 2022 17th Annual System of Systems Engineering Conference (SOSE), 2022;37–42. <https://doi.org/10.1109/SOSE55472.2022.9812687>.
61. Park J, Bae J, Lim J, Kim B, Jeong J. Led-display defect detection based on yolov5 and transformer. *IEEE Access*. 2023;11:124660–75. <https://doi.org/10.1109/ACCESS.2023.3325487>.
62. Park H, Kang Y, Choi S-K, Park HW. Quality evaluation modeling of a ded-processed metallic deposition based on resnet-50 with few training data. *Journal of Intelligent Manufacturing*, 2024;1–17 <https://doi.org/10.1007/s10845-024-02408-0>.
63. Shaloo M, Princz G, Hörbe R, Erol S. Flexible automation of quality inspection in parts assembly using cnn-based machine learning. *Procedia Comput Sci*. 2024;232:2921–32. <https://doi.org/10.1016/j.procs.2024.02.108>.
64. Ha H, Jeong J. Cnn-based defect inspection for injection molding using edge computing and industrial iot systems. *Appl Sci*. 2021;11:6378. <https://doi.org/10.3390/app11146378>.
65. Vaheer K, Mahmood K, Otto T, Riives J. Simulation based feasibility analysis of autonomously movable robot arm. *IOP Conf Ser Mater Sci Eng*. 2021;1140: 012055. <https://doi.org/10.1088/1757-899X/1140/1/012055>.
66. Wiedholz A, Wucherer S, Dietrich S, Kerber F. Semantic 3d scene segmentation for robotic assembly process execution. In: 2023 IEEE 19th International Conference on Automation Science and Engineering (CASE), 2023;1–6. <https://doi.org/10.1109/CASE56687.2023.10260532>.
67. Vukicevic AM, Djapan M, Todorovic P, Eric M, Stefanovic M, Macuzic I. Decision support system for dimensional inspection of extruded rubber profiles. *IEEE Access*. 2019;7:112605–16. <https://doi.org/10.1109/ACCESS.2019.2934561>.
68. Yadav P, Uikey M, Lonkar P, Kayande S, Maurya A. Sorting of objects using image processing. In: 2020 IEEE International Conference for Innovation in Technology (INOCON), 2020;1–6. <https://doi.org/10.1109/INOCON50539.2020.9298360>.
69. Xing K, Liu X, Liu Z, Mayer JRR, Achiche S. Low-cost precision monitoring system of machine tools for smes. *Procedia CIRP*. 2021;96:347–52. <https://doi.org/10.1016/j.procir.2021.01.098>.
70. Lin C, Fujimura S. A general product identification method for mass customization based on deep learning. In: 2021 China Automation Congress (CAC), 2021;883–890. <https://doi.org/10.1109/CAC53003.2021.9728701>.
71. Mukhopadhyay A, Murthy LR, Arora M, Chakrabarti A, Mukherjee I, Biswas P. PCB Inspection in the Context of Smart Manufacturing: Proceedings of ICORd 2019 2019;1:655–663. https://doi.org/10.1007/978-981-13-5974-3_57.
72. Vukicevic A, Mladineo M, Banduka N, Macuzic I. A smart warehouse 4.0 approach for the pallet management using machine vision and internet of things (iot): a real industrial case study. *Adv Prod Eng Manag*. 2021;16:297–306.
73. Ahmad R, Plapper P. Safe and automated assembly process using vision assisted robot manipulator. *Procedia CIRP*. 2016;41:771–6. <https://doi.org/10.1016/j.procir.2015.12.129>.
74. Kim D, Seo S, Yoo N, Shin G. A study on sample size sensitivity of factory manufacturing dataset for cnn-based defective product classification. *Computation*. 2022;10:142. <https://doi.org/10.3390/computation10080142>.
75. Zhou J, Hartman N. Development and evaluation of a vision inspection system for plastic bottle measurement, 2024;41–50. <https://doi.org/10.4028/p-HPT9vc>.
76. Park S-Y, Kim H, Ahn S-H. Hand-monitoring system using cutmix-based synthetic augmentation for safety in factories. *IEEE Access*. 2024. <https://doi.org/10.1109/ACCESS.2024.3367805>.
77. Block L, Raiser A, Schön L, Braun F, Riedel O. Image-bot: Generating synthetic object detection datasets for small and medium-sized manufacturing companies. *Procedia CIRP*. 2022;107:434–9. <https://doi.org/10.1016/j.procir.2022.05.004>.
78. Zhou Z, Li L, Fürsterling A, Durocher HJ, Mouridsen J, Zhang X. Learning-based object detection and localization for a mobile robot manipulator in sme production. *Robot Comput-Integr Manuf*. 2022;73: 102229. <https://doi.org/10.1016/j.rcim.2021.102229>.
79. Polonara M, Romagnoli A, Biancini G, Carbonari L. Introduction of collaborative robotics in the production of automotive parts: a case study. *Machines*. 2024;12:196. <https://doi.org/10.3390/machines12030196>.
80. Group K. KfW-ifo Skilled Labour Barometer: Skills shortage became much more severe in the spring. Accessed: 2024-11-29 2021. https://www.kfw.de/About-KfW/Newsroom/Latest-News/Pressemitteilungen-Details_654144.html.
81. Deniša M, Ude A, Simonič M, Kaarlela T, Pitkäaho T, Pieskä S, Arents J, Judvaitis J, Ozols K, Raj L, Czmerk A, Dianatfar M, Latokartano J, Schmidt P, Mauersberger A, Singer A, Arnarson H, Shu B, Dimosthenopoulos D, Lanz M. Technology modules providing solutions for agile manufacturing. *Machines*. 2023;11:877. <https://doi.org/10.3390/machines11090877>.
82. Ivanovska T, Reich S, Bevec R, Gosar Z, Tamosiunaite M, Ude A, Wörgötter F. Visual inspection and error detection in a reconfigurable robot workcell: an automotive light assembly example, 2018;607–615. <https://doi.org/10.5220/0006666506070615>.
83. Simeth A, Kumar AA, Plapper P. Flexible and robust detection for assembly automation with yolov5: a case study on hmlv manufacturing line. *J Intell Manuf*. 2024. <https://doi.org/10.1007/s10845-024-02411-5>.
84. Singh SA, Kumar AS, Desai KA. Comparative assessment of common pre-trained cnns for vision-based surface defect detection of machined components. *Expert Syst Appl*. 2023;218: 119623. <https://doi.org/10.1016/j.eswa.2023.119623>.
85. Li C, Bian S, Wu T, Donovan RP, Li B. Affordable artificial intelligence-assisted machine supervision system for the small and medium-sized manufacturers. *Sensors*. 2022. <https://doi.org/10.3390/s22166246>.
86. Sahay A, Biswas P, Arora M, Chakrabarti A, Kannaraya P. G H, S. Designing an affordable system for early defect detection using image processing. 2020. <https://doi.org/10.3233/ATDE190022>.
87. Ullah U, Bhatti FA, Maud AR, Asim MI, Khurshid K, Maqsood M. Iot-enabled computer vision-based parts inspection system for sme 40 Microprocessors and Microsystems 2021;87:104354. <https://doi.org/10.1016/j.micpro.2021.104354>.

88. Vaher K, Otto T, Riives J. Positioning error correction of autonomously movable robot arm. *J Mach Eng.* 2020. <https://doi.org/10.36897/jme/129013>.
89. Ahmed K, Jia G, Chen Y, Ding C, Wen Z, Mei S. Edge intelligent for smart factory application. In: 2022 2nd International Conference on Computer, Control and Robotics (ICCCR), 2022;14–19. <https://doi.org/10.1109/ICCCR54399.2022.9790194>.
90. Horputra P, Phrajonthong R, Kaewprapha P. Deep learning-based bottle caps inspection in beverage manufacturing and packaging process. In: 2021 9th International Electrical Engineering Congress (IEECON), 2021;499–502. <https://doi.org/10.1109/IEECON51072.2021.9440326>.
91. Brezani S, Hrasko R, Vojtas P. Smart extensions to regular cameras in the industrial environment. *Procedia Comput Sci.* 2022;200:298–307. <https://doi.org/10.1016/j.procs.2022.01.228>.
92. Kubik C, Molitor DA, Varchmin S, et al. Image-based feature extraction for inline quality assurance and wear classification in high-speed blanking processes. *Int J Adv Manuf Technol.* 2023;129(11–12):4883–97. <https://doi.org/10.1007/s00170-023-12653-x>.
93. Bélisle JM, Dubé F, Blais L, Chénard D, Martel P. Optical profilometry based on light microscopy. In: 2016 Photonics North (PN), 2016;1–2. <https://doi.org/10.1109/PN.2016.7537901>.
94. Yong-Jun I, Jae-Hyeon L, Jae-Un L, Tai-Woo C. Application of image classification model to improve visual inspection systems of industrial cutters. *Int J Innov Comput Inf Control Express Lett.* 2023;14(3):257–63. <https://doi.org/10.24507/ijicelb.14.03.257>.
95. Gunal MM. In: Gunal MM. (ed.) *Data Collection Inside Industrial Facilities with Autonomous Drones*, 2019;141–151. Springer, Cham. https://doi.org/10.1007/978-3-030-04137-3_9.
96. Voutsinas S, Karolidis D, Voyiatzis I, Samarakou M. Development of an iot power management system for photovoltaic power plants. In: 2022 11th International Conference on Modern Circuits and Systems Technologies (MOCASST), 2022;1–5. <https://doi.org/10.1109/MOCASST54814.2022.9837652>.
97. Mohd Saad N, Abdullah AR, Hasan W, Abdul Rahman NN, Ali N, Abdullah I. Automated vision based defect detection using gray level co-occurrence matrix for beverage manufacturing industry. *IAES Int J Artif Intell (IJ-AI).* 2021;10:818. <https://doi.org/10.11591/ijai.v10.i4.pp818-829>.
98. Rao V, Singh M. Low-cost computer vision based real-time 3d localization of object for robotic applications. In: 2018 15th IEEE India Council International Conference (INDICON), 2018;1–6. <https://doi.org/10.1109/INDICON45594.2018.8987194>.
99. Ardhy F, Hariadi FI. Development of sbc based machine-vision system for pcb board assembly automatic optical inspection. In: 2016 International Symposium on Electronics and Smart Devices (ISESD), 2016;386–393. <https://doi.org/10.1109/ISESD.2016.7886753>.
100. Abdul Rahman NN, Mohd Saad N, Abdullah AR, Hassan MRM, Mohamad Basir MSS, Noor N. Automated real-time vision quality inspection monitoring system. *Indonesian J Electric Eng Comput Sci.* 2018;11:775–83. <https://doi.org/10.11591/ijeecs.v11.i2.pp775-783>.
101. Bian SJ. Machine learning-based real-time monitoring system for smart connected worker to improve energy efficiency. *J Manuf Syst.* 2021;61:66–76. <https://doi.org/10.1016/j.jmsy.2021.08.009>.
102. Wassermann J, Vick A, Krüger J. Intuitive robot programming through environment perception, augmented reality simulation and automated program verification. *Procedia CIRP.* 2018;76:161–6. <https://doi.org/10.1016/j.procir.2018.01.036>. (7th CIRP Conference on Assembly Technologies and Systems (CATS 2018)).
103. Bevec R, Gašpar T, Ude A. Robot-Driven Autofocus Control Mechanism for an In-hand Fixed Focus Camera: Proceedings of the 27th International Conference on Robotics in Alpe-Adria Danube Region (RAAD 2018), 2019;551–559. https://doi.org/10.1007/978-3-030-00232-9_58.
104. Zhang M, Zhang Z, Lotfi N, Esche S. Development of automatic reconfigurable robotic arms using vision-based control. 2017. <https://doi.org/10.18260/1-2-28170>.
105. Mohamad Anas N, Yusof M, Aziz M. Machine tool condition monitoring system: A review on feasible solution, 2022;1–4. <https://doi.org/10.1109/ICALoT57170.2022.10121847>.
106. Eissa A, Atia M, Roman M, Eissa A, Roman M. An effective programming by demonstration method for smes' industrial robots. *J Mach Eng.* 2020;20(4):86–98. <https://doi.org/10.36897/jme/130944>.
107. Hatano T, Horvath CM, Thomessen T, Niitsuma M. A vibrotactile navigation aid for remote operation of an industrial robot. In: 2016 IEEE/SICE International Symposium on System Integration (SII), 2016;700–705. <https://doi.org/10.1109/SII.2016.7844081>.
108. Shu B, Solvang B. Architecture for task-dependent human-robot collaboration, 2021;207–212. <https://doi.org/10.1109/IEEECONF49454.2021.9382703>.
109. Sommer M, Stjepandić J, Stobrawa S, Soden M. Automated generation of digital twin for a built environment using scan and object detection as input for production planning. *J Ind Inf Integr.* 2023;33: 100462. <https://doi.org/10.1016/j.jii.2023.100462>.
110. Yang X, Zhou Z, Sørensen JH, Christensen CB, Ünal M, Zhang X. Automation of sme production with a cobot system powered by learning-based vision. *Robot Comput-Integr Manuf.* 2023;83: 102564. <https://doi.org/10.1016/j.rcim.2023.102564>.
111. Hong S, Lee K. An autonomous operational service system for machine vision-based inspection towards smart factory of manufacturing multi-wire harnesses. *J Inf Commun Convergence Eng.* 2022;20:317–25. <https://doi.org/10.56977/jicce.2022.20.4.317>.
112. Wang J, Li P, Luo L, Sun H. Design and development of intelligent inventory system for small and micro enterprise warehousing. In: 2023 4th International Conference on Computer, Big Data and Artificial Intelligence (ICCBD+AI), 2023;281–285. <https://doi.org/10.1109/ICCBD-AI62252.2023.00053>.
113. Soundattikar SA, Naik VR, Adake CV. Component handing automated guided vehicle-a cyber physical system case study. In: 2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), 2022;1–6. <https://doi.org/10.1109/ICAECT54875.2022.9808022>.
114. Bu Y, Guo J. The online detection system of concentric ring size based on machine vision. *J Phys Conf Ser.* 2022. <https://doi.org/10.1088/1742-6596/2290/1/012108>.
115. Schmelter T. Evaluating cad usage to generate synthetic images for machine learning-based object detection. In: *Lecture Notes in Networks and Systems*, 2024;Part F1764:14–23. https://doi.org/10.1007/978-3-031-47394-4_2.