Computer Vision in Manufacturing for Missing Object Detection: A Survey

Betsy Villa, Ian Gibson, and Estefanía Talavera

***Abstract*— Computer vision plays a key role in modern manufacturing, where effective quality assurance is essential for operational efficiency. Recent advances in integrating machine learning and deep learning have enabled automated object detection, anomaly detection, and defect classification. This survey focuses on missing object detection in manufacturing, covering methods from traditional image processing to advanced deep learning approaches. Emerging paradigms, including edge computing and explainable AI, are discussed in the context of low-latency decision making and IoT integration. Key challenges such as data scarcity, system integration, and environmental variability are analyzed alongside recent solutions. Despite progress, the limited availability of dedicated datasets and the need for robust and generalizable models remain major challenges. This work highlights current trends and outlines future directions toward reliable and efficient inspection systems aligned with Industry 4.0.**

***Index Terms*— Industry 4.0, Manufacturing, Missing Part Detection, Object Detection, Quality Control, Smart Manufacturing**

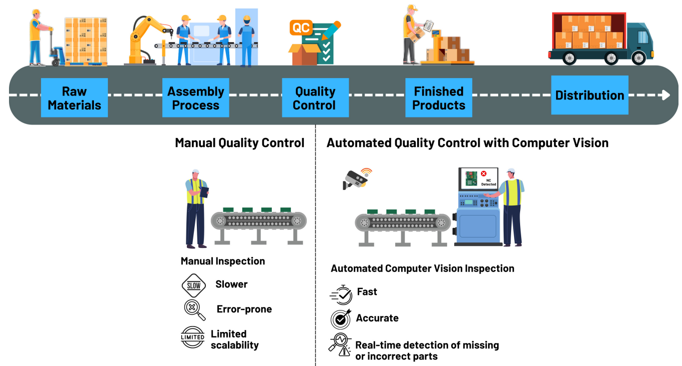

Fig. 1. Quality Control and Automation in Manufacturing. The figure presents a comparison between traditional manual inspection, characterized by reduced throughput, susceptibility to human error, and constrained scalability, and automated inspection based on computer vision techniques, which supports real-time identification of missing or nonconforming components with substantially higher processing speed and consistency. This contrast underscores and motivates the adoption of the computer vision methodologies reviewed in the present study.

I. Introduction

In modern manufacturing processes, ensuring high product quality is essential for maintaining competitiveness and operational efficiency. Identifying faults, particularly missing or incorrectly assembled components, remains a critical challenge in industrial production. Poor quality can account for 1% to 40% of total manufacturing costs [1], driven by factors such as supply chain disruptions, inconsistent processes, and human error.

A key aspect of quality control is the reliable detection of missing components during assembly. Traditional inspection techniques, while still widely used, often lack consistency and require significant manual effort. As a result, manufacturers are increasingly adopting automated solutions based on computer vision (CV) and machine learning (ML) to improve inspection accuracy, speed, and repeatability. This shift aligns with the broader adoption of Industry 4.0 technologies, particularly in sectors such as automotive manufacturing, although challenges remain, including high implementation costs and a shortage of skilled personnel [2].

The rapid advancement of deep learning, especially convolutional neural networks (CNNs), has significantly enhanced the performance of CV systems in tasks such as defect detection, object recognition, and segmentation [3]. As illustrated in Fig. 1, a typical industrial CV pipeline integrates image acquisition, preprocessing, feature extraction, and decision making stages to enable automated inspection. These systems are now widely deployed across manufacturing domains, including automotive, electronics, and pharmaceutical industries, where high precision and reliability are required.

Despite these advances, several challenges limit the full deployment of CV systems in real world manufacturing environments. These include limited availability of labeled defect data, variability in operating conditions, high computational requirements, and difficulties in integrating CV solutions into existing production systems.

Missing object detection differs fundamentally from general defect detection; rather than identifying surface level anomalies on components already present, it requires contextual reasoning about assembly completeness, verifying whether expected components occupy their correct positions relative to a reference state. In table I, no prior survey addresses this problem as a primary focus. This work fills that gap by reviewing traditional CV, deep learning, hybrid, and anomaly

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TABLE I
COMPARISON OF EXISTING SURVEYS ON COMPUTER VISION IN MANUFACTURING

Survey	Year	Main Focus	Methods Covered	Industrial Coverage	Missing Obj.	Datasets
Yang et al. [4]	2020	DL for defect detection	CNN based methods	Manufacturing inspection	No	Mentioned but not evaluated
Yang et al. [5]	2021	DL for manufacturing defect detection	DL	Manufacturing defect detection	No	Mentioned but not evaluated
Ren et al. [6]	2022	Machine vision defect detection	Object detection techniques	General manufacturing	No	Mentioned but not evaluated
Zhou et al. [7]	2023	CV techniques in manufacturing	Image processing, ML, DL	Broad manufacturing tasks	No	Mentioned but not evaluated
Sharma et al. [8]	2023	Bibliometric analysis of CV research	Research trend analysis	General manufacturing research	No	No
Mohandas et al. [9]	2024	Incremental DL for defect detection	Incremental learning, catastrophic forgetting mitigation	Manufacturing inspection & re-manufacturing	No	Mentioned but not evaluated
Hutten et al. [10]	2024	DL for automated visual inspection	CNN architectures	Manufacturing inspection systems	No	Mentioned but not evaluated
Kühlechner [11]	2025	OD methods for industrial quality control	One stage, two stage, transformer, hybrid detectors	Automotive, electronics, packaging, aerospace	No	Comparative Analysis
This Work	**2026**	**Missing object detection in manufacturing**	**Traditional CV, ML, DL, Hybrid**	**Assembly inspection and quality control**	**Yes**	**Comparative Analysis**

detection methods for missing object detection, alongside emerging paradigms and public datasets evaluated for assembly verification suitability.

The literature review was conducted using IEEE Xplore, Scopus, and Google Scholar between 2018 and 2025. Search terms included "missing object detection manufacturing," "assembly verification computer vision," and related keywords. Peer-reviewed studies relevant to industrial inspection, anomaly detection, and assembly verification were prioritized, while non-industrial and non-English publications were excluded.

II. COMPUTER VISION IN MANUFACTURING

CV enables machines to extract meaningful information from visual data [12]. In manufacturing, its effectiveness depends on meeting strict requirements, including real-time processing, robustness to environmental variability, and operation with limited annotated data. Unlike general purpose vision tasks, industrial applications demand high reliability, low latency, and resilience to noise, occlusion, and domain shifts.

The evolution of CV in manufacturing (Fig. 2) reflects a transition from rule based systems to data driven approaches. Early systems relied on handcrafted features and simple inspection rules, offering computational efficiency but limited robustness to industrial variability [13].

In the 1980s and early 1990s, advances in image processing enabled contour detection, segmentation, and feature extraction [14], [15], while early surveys [16]–[18] highlighted the growing role of machine vision in industrial inspection. However, these methods remained sensitive to noise and required controlled environments.

By the late 1990s, ML and 3D imaging improved inspection capabilities by incorporating spatial information [19], [20]. Applications expanded to high speed inspection and PCB analysis [21]–[23], but systems still depended heavily on manual feature engineering and lacked generalization [24], [25].

The 2000s introduced real-time processing enabled by advances in hardware and imaging systems [26]–[29]. Integration with internet of things (IoT) further supported real-time monitoring and decision making [30], although challenges related to latency, synchronization, and system integration emerged.

The adoption of deep learning (DL), particularly CNNs, marked a major breakthrough by enabling automatic feature learning and significantly improving detection accuracy and robustness [31], [32]. Models such as you only look once (YOLO) and region-based CNN (R-CNN) demonstrated strong performance in object detection and inspection tasks [33]. However, these approaches require large annotated datasets and substantial computational resources, limiting their deployment in industrial environments.

Recent research trends focus on explainable AI (XAI) [34], edge computing [35], and smart inspection systems [36]. Edge based CV reduces latency by processing data closer to the source, while XAI improves transparency and trust in automated decisions. Nevertheless, balancing accuracy, interpretability, and low latency performance remains a key challenge.

Several recent surveys [4]–[11] provide broad overviews of CV in manufacturing, primarily focusing on defect detection and general inspection tasks. As summarized in Table I, these works provide limited coverage of missing object detection and assembly verification, which are the primary focus of this survey.

From an application perspective, CV systems have demonstrated strong potential in industrial environments [37]–[40]. For example, [41] developed a real-time system for detecting missing components on printed circuit boards, highlighting the practical relevance of these methods.

Modern inspection systems integrate imaging hardware, lighting, and learning based models to detect defects and verify assembly completeness [42]. Common approaches include object detection and anomaly detection using models such

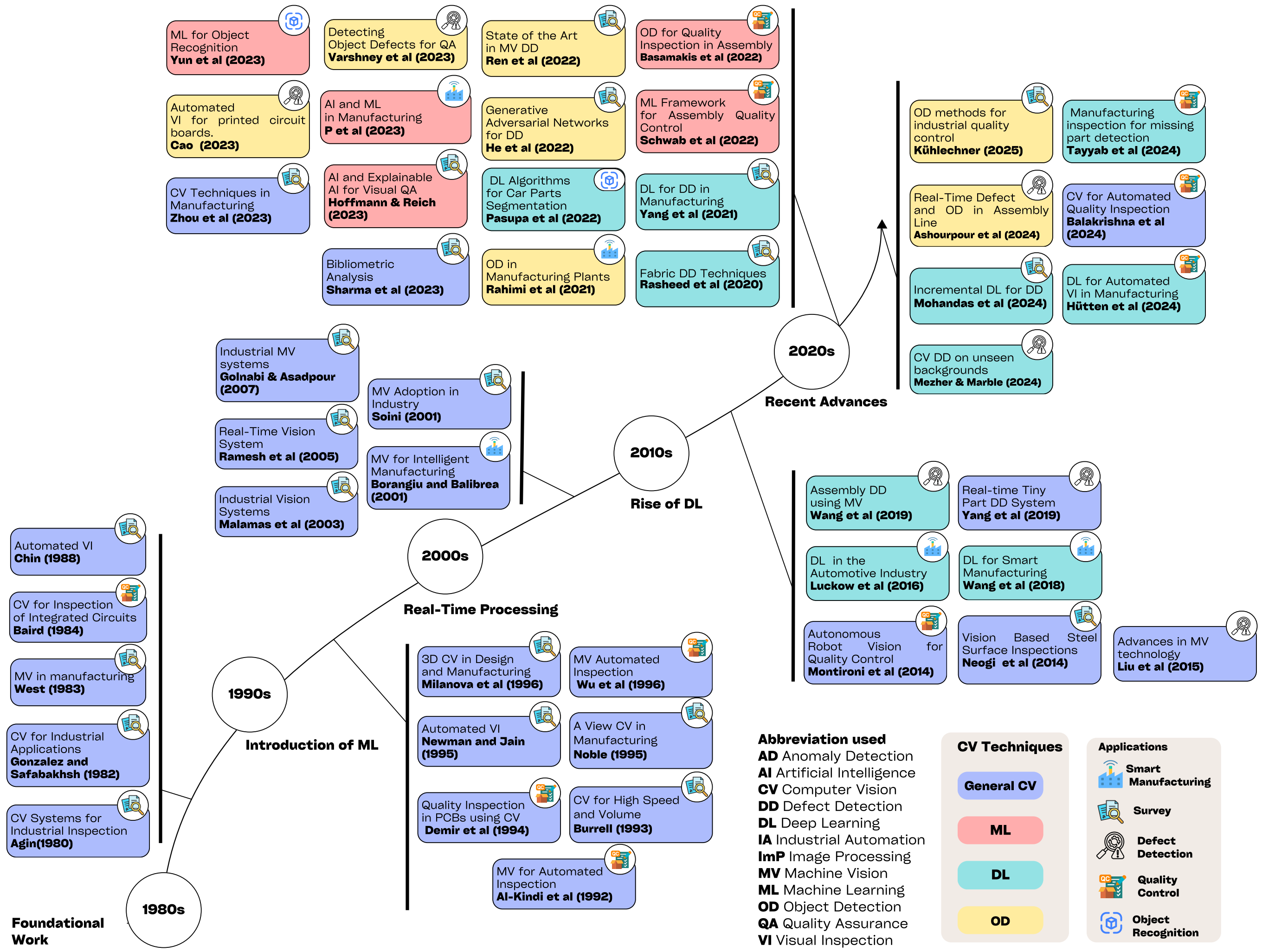

Fig. 2. Historical Overview: Missing Object Detection in Manufacturing. The timeline illustrates the evolution of CV from early image processing methods in the 1980s to machine learning in the 1990s, real-time systems in the 2000s, deep learning in the 2010s, and recent advances, including explainable AI and edge-integrated solutions.

as YOLO [43]–[45], Faster R-CNN [46], SSD [47], and RetinaNet [48]. While effective, their performance depends on dataset quality, task complexity, and real-time constraints. Despite significant progress, detecting missing or incorrectly assembled components remains challenging. This task requires not only accurate object localization but also contextual understanding of assembly processes, which standard detection models do not fully address.

Overall, the evolution of CV in manufacturing highlights a trade-off between accuracy, efficiency, and robustness. Although deep learning has significantly improved performance, challenges related to data dependency, real-time deployment, and generalization persist, particularly for missing object detection in complex industrial environments.

III. Methodologies for Missing Object Detection

A. Methods

a) Traditional Image Processing Methods: Traditional methods, such as those using OpenCV and thresholding algorithms, have long served as the foundation of missing object detection in manufacturing [61]. These approaches rely on predefined rules such as edge detection, color inspection, and shape analysis, making them computationally efficient and suitable for real-time applications with limited hardware resources [62]. However, they are highly sensitive to variations in lighting, object positioning, and background complexity. As a result, their performance degrades significantly in dynamic industrial environments, limiting their applicability to controlled settings.

b) Machine Learning Architectures: Recent advances in DL, particularly CNNs, have transformed missing object detection by enabling automatic feature extraction from large-scale datasets. Modern architectures such as YOLO and R-CNN exhibit distinct trade-offs in performance.

YOLO models prioritize real-time inference and are widely adopted in manufacturing due to their ability to meet strict latency requirements. In contrast, R-CNN variants achieve higher localization accuracy but incur increased computational complexity. Despite their advantages, YOLO models may degrade in performance in scenarios involving small objects, occlusions, or complex assembly configurations.

TABLE II
PERFORMANCE COMPARISON OF REPRESENTATIVE DETECTION METHODS ACROSS INDUSTRIAL DATASETS

Method	Type	Dataset	Performance Metric	Speed	Robustness
YOLOv8 [43]	One-stage	Assembly / manufacturing	mAP: 99%	RT	High (noise, moderate occlusion)
YOLOv5 [44], [49], [50]	One-stage	PCB, weld, QC	Acc.: $\sim$ 98%, Prec.: 0.92–0.97	NRT	High (noise, illumination variation)
Faster R-CNN [46], [51], [52]	Two-stage	Assembly / manufacturing	mAP > 84%, Acc.: up to 96.3%	Offline	Moderate–High (occlusion, complex scenes)
Mask R-CNN [53], [54]	Two-stage	Assembly inspection	Acc.: 87.5–96%, F1: up to 89%	Offline	High (occlusion, segmentation)
Hybrid (CNN + SVM / RGB-D) [55], [56]	Hybrid	Complex industrial setups	Acc.: 81.7–95%, F1: up to 95%	NRT	High (multimodal, occlusion)
Autoencoder / anomaly detection [57], [58]	Unsupervised	MVTec AD	AUC: $\sim$ 0.90–0.99	NRT	High (anomaly patterns, limited occlusion)
Action-based models [59], [60]	Temporal	Assembly101 / IndustReal	F1: $\sim$ 0.78–0.85, mIoU: up to 0.85	NRT	Moderate–High (temporal variation, occlusion)

Note: Speed is categorized based on inference latency, where real-time (RT) corresponds to $< 50\,\mathrm{ms}$*, near real-time (NRT) to* 50–$150\,\mathrm{ms}$*, and offline processing to* $> 150\,\mathrm{ms}$*. Robustness reflects the ability to maintain performance under real-world industrial conditions, including noise, occlusion, illumination changes, domain shifts, and cluttered environments.* Reported performance values are derived from different datasets, evaluation protocols, and metric definitions; therefore, direct numerical comparison across methods is not intended. The table provides indicative performance ranges within each method category rather than a cross-method ranking.

For instance, [43] implemented a real-time YOLOv8 system for detecting assembly defects in a chainsaw production line, demonstrating its effectiveness in industrial settings. Similarly, [44] proposed a YOLOv5 model for object and defect detection, although its validation in real industrial environments remains limited. Moreover, [63] proposed an improved YOLOv5s model for track defect detection, achieving enhanced performance in complex inspection scenarios. Finally, [45] presented a YOLOv4 approach, demonstrating strong performance across multiple manufacturing processes.

Further studies highlight the adaptability of DL models across diverse applications. For instance, [64] applied YOLO based architectures to detect defects on metal surfaces, while [46] used CAD/pose based alignment, in which 3D CAD models serve as reference templates for verifying component presence and spatial configuration, and employed Faster R-CNN in conjunction with 3D CAD models to assess assembly integrity, these works collectively illustrate that model performance is strongly influenced by both task complexity and data representation.

c) Hybrid Models: Hybrid approaches combine traditional image processing techniques with ML models to balance interpretability and performance. These methods can improve robustness in complex industrial environments by leveraging complementary features from multiple sources. Examples include multi-normalized cross correlation and truncated shape-based matching [65], Mask R-CNN combined with Support Vector Machines (SVM) for assembly inspection [66], and modified Faster R-CNN architectures incorporating both RGB and depth data [56].

While hybrid approaches can enhance detection performance, they often introduce additional system complexity and require careful feature engineering compared to end-to-end DL methods. Their effectiveness is therefore highly dependent on system design and integration strategies. In contrast, fully DL approaches, such as the anomaly detection model proposed in [67], offer end-to-end learning capabilities but require large annotated datasets.

Recent hybrid learning approaches further improve inspection performance by combining data driven models with domain adaptation strategies. For instance, [68] proposed an augmented hybrid learning framework for defect inspection in hydrogen storage manufacturing, demonstrating improved robustness under real-world industrial conditions.

d) Advancements in Anomaly Detection: Anomaly detection methods focus on identifying deviations from expected patterns, providing an alternative formulation for missing object detection. Classical approaches include Isolation Forest, Local Outlier Factor (LOF), One-Class Support Vector Machine (SVM), and K-means clustering [9], [69]. These methods are effective for detecting outliers but are limited in capturing complex spatial relationships in assembly tasks.

Recent advances in supervised anomaly detection have substantially enhanced performance in industrial applications. For instance, segmentation anomaly detectors (SegADs) applied to datasets such as the Valeo Anomaly Dataset (VAD) have exhibited strong capabilities in identifying both known and previously unseen faults [70]. Complementary supervised approaches include 3D metrology systems for detecting dimensional deviations [71], convolutional autoencoders for anomaly detection in metal stamped components [72], anomaly segmentation methods for quality inspection of industrial PET preforms [73] and minimal-shot anomaly detection approaches based on transformer and graph attention architectures which can be used to improve generalization under limited labeled data conditions [74].

In contrast, unsupervised anomaly detection methods typically exploit pretrained feature representations and adversarial learning. For example, [75] proposed a feature mapping based framework for anomaly segmentation, whereas [5] introduced an adversarial feature editing approach designed to improve defect detection in textured industrial surfaces.

Despite these advances, anomaly detection methods are not explicitly designed for detecting missing objects and may struggle to distinguish between acceptable variations and true assembly errors without contextual modeling.

e) Assembly State Recognition and Change Detection: Assembly state recognition and change detection represent emerging approaches for missing object detection in complex manufacturing processes. The StateDiffNet framework [76] combines assembly state recognition with change detection by comparing expected and observed configurations.

Unlike traditional object detection methods, this approach focuses on structural differences rather than individual components, enabling more effective detection of missing or incorrectly assembled parts in complex scenarios.

By modeling discrepancies between reference and current assembly states, it improves generalization to unseen configurations. However, it relies on accurate reference models and alignment mechanisms and may introduce additional computational overhead.

f) Comparative Analysis: The results summarized in Table II highlight clear trade-offs between detection accuracy, computational efficiency, and robustness. One stage detectors, such as YOLOv5 and YOLOv8, achieve real-time performance and are well suited for high-throughput production environments. In contrast, two stage detectors, such as Faster R-CNN and Mask R-CNN, offer higher localization accuracy but are constrained by their inference latency. Hybrid approaches improve robustness in complex industrial settings, particularly when multimodal data are available, but often increase system complexity. Anomaly detection methods perform well on structured datasets but are not directly applicable to missing object detection tasks. These trade-offs indicate that no single method is universally optimal, and the selection of an appropriate approach depends on application specific constraints, including dataset characteristics, real-time requirements, and assembly complexity.

B. Dataset

Datasets are essential for developing robust CV systems for missing object detection in manufacturing; however, existing public datasets remain limited in scale, diversity, and annotation completeness. As summarized in Table III, current datasets span applications such as assembly (IndustReal [60], Assembly101 [59]), defect detection (VAD [70], CarDD [77], DeepPCB [78]), component inspection (Latch Mechanism Test [79], PCB [80]) and anolmaly detection (Real-IAD [81], CAD100K [82], MVTec AD [58]).

Despite this diversity, most datasets are designed for defect or anomaly detection rather than explicit missing object detection. Only a few datasets, such as IndustReal, Latch Mechanism Test, Real-IAD, and CAD100K, provide annotations suitable for assembly verification tasks. Furthermore, many datasets are relatively small and domain specific, limiting generalization across production settings.

To mitigate these limitations, synthetic data generation and augmentation techniques have been explored [83], [84]. Nevertheless, there remains a clear need for large scale, diverse, and well annotated datasets specifically designed for missing object detection, including multimodal data and explicit annotations of component presence and absence.

C. Emerging Paradigms in CV for Manufacturing

Recent advances in CV for manufacturing extend beyond conventional CNNs, incorporating transformer architectures, multimodal sensing, self-supervised learning, and domain adaptation. Although many of these directions are still in relatively early stages of industrial adoption, their importance in modern industrial vision systems is increasing significantly. These paradigms address key limitations related to data scarcity, robustness, and real-time deployment in missing object detection.

a) Vision Transformers: Vision Transformers (ViTs) leverage global self attention to capture long range dependencies, improving robustness in noisy and data limited environments [87], [88]. Reported results show high accuracy (92-100%) with real-time performance (18.5-52 FPS), outperforming CNNs by up to 17% under challenging conditions. Detection oriented variants such as DETR and RT-DETR further simplify pipelines by removing anchor design and non maximum suppression. However, their computational cost remains a limitation, motivating lightweight, hybrid, and quantization friendly architectures for edge deployment [89], [90]. These architectures are increasingly explored to balance latency, accuracy, and energy efficiency in embedded manufacturing systems.

b) Multimodal RGB-D Fusion: Combining RGB and depth data improves robustness to occlusion and illumination changes. RGB-D extensions of Faster R-CNN achieve up to 13% mAP improvement over RGB only models [91], while attention based fusion networks consistently outperform unimodal approaches [92]. Cross modal learning with pretrained models further enhances generalization across heterogeneous data sources [93].

c) Self-Supervised Learning: Self-supervised learning reduces reliance on labeled data by leveraging unlabeled samples. Methods such as SEDD achieve high anomaly detection performance (AUC up to 98.4%) [94], while self-supervised ViTs reach up to 99.8% accuracy across varying conditions [88]. Approaches such as CutPaste improve performance on industrial datasets (e.g., MVTec AD) [95], making them well suited for missing object detection where labeled data are scarce.

d) Federated Learning: Federated learning enables distributed model training without sharing raw data, addressing privacy and intellectual property constraints [96]. Edge based federated frameworks improve generalization across production sites [97], although challenges remain in communication overhead and real time integration.

e) Synthetic-to-Real Transfer: Synthetic data generation and domain adaptation mitigate data scarcity in industrial settings. Methods such as DD-Aug improve detection accuracy by up to 10% [98], while synthetic to real adaptation enhances performance across domains [99]. These approaches enable scalable training for missing object detection without extensive manual annotation.

TABLE III
REPRESENTATIVE PUBLIC DATASETS FOR CV IN MANUFACTURING AND THEIR SUITABILITY FOR MISSING OBJECT DETECTION

Dataset	Year	Size	Resolution	Industrial Sector	Annotation Type	Label Quality	Domain Diversity	Missing Object Suitability
CAD100K [82]	2026	100000 images	Variable	Automotive	Multi level annotations	✓	✓	✓
Real-IAD [81]	2024	150000 images	Variable	Industrial Inspection	Image classification, pixel level localization	✓	✓	✓
IndustReal [60]	2024	84 videos	1280×720	General assembly	Action recognition, assembly states	✓	∼	✓
VAD [70]	2024	5000 images	512×512	Industrial inspection	Defect classification	✓	∼	✗
CarDD [77]	2023	4000 images	Variable	Automotive	Damage categories	✓	∼	✗
Latch Mech Test [79]	2023	380 images	640×640	Mechanical assembly	Missing component labels	∼	✗	✓
Assembly101 [59]	2022	4321 videos	1920×1080	Assembly operations	Procedural actions	✓	✓	✗
PCB [80]	2022	672 images	Variable	Electronics manufacturing	Electronic component labels	✓	✗	∼
DeepPCB [78]	2019	1500 images	640×640	Electronics manufacturing	PCB defect labels	∼	✗	✗
Delft Bikes [85]	2021	10000 images	640×480	Consumer products	Part states	∼	✓	∼
AutoVI [86]	2021	3950 images	400×400	Automotive inspection	Pixel level segmentation	✓	∼	✗
MVTec AD [58]	2019	5000 images	700-1024	Industrial objects	Pixel level anomaly masks	✓	∼	✗

Note: ✓ = Adequate, ∼ = With potential for adaptation, ✗ = Not adequate.

f) Edge Intelligence: Edge based CV systems process data locally, reducing latency and enabling real-time inspection. Frameworks such as IndustrialEdgeML achieve end-to-end processing with latencies below 100 ms on embedded devices [100], making them suitable for high throughput manufacturing environments.

IV. APPLICATIONS OF CV IN MANUFACTURING

CV techniques have become essential in manufacturing; however, their effectiveness varies significantly across industries depending on task complexity, data availability, and real-time requirements. The application areas of CV include the automotive, electronics, and pharmaceutical industries due to the high impact of missing elements in the final manufactured objects. CV applications include surface inspection, automated defect detection, and online quality control [101]. These technologies not only enhance product quality but also reduce labor costs and improve production consistency [102]. Common CV methods in manufacturing include feature detection, recognition, segmentation, and 3D modeling [7]. Machine vision systems that integrate cameras, lighting, and image processing algorithms play a crucial role in industrial inspections [103]. In the pharmaceutical industry, CV is used for powder characterization, crystallization monitoring, and tablet coating inspection [104]. Recent advances in DL have further enhanced the accuracy and adaptability of CV quality control systems in manufacturing [105].

a) Industry Specific Applications: CV applications in manufacturing enhance quality control by identifying defects and anomalies [106]. This section focuses on three main industries: automotive, electronics, and pharmaceutical.

Automotive Industry: Deep neural networks and advanced single-shot detectors are employed to detect surface imperfections and assembly errors [107], missing part detection [108], and nonconformity detection for defect identification [109].

Electronics Industry: DL methods are particularly widely used, especially for high precision tasks such as PCB inspection. Systems often utilize YOLO, Faster R-CNN, and autoencoder architectures in PCB inspection [110]; component placement task [111]; and anomaly detection [112].

Pharmaceutical Industry: A combination of DL and traditional methods focuses on particle detection and product integrity. CV techniques consistently achieve high performance in particle inspection, tablet integrity evaluation, and packaging defect detection [113] [114].

Although DL techniques dominate across industries, their performance is highly task dependent. For example, high-precision tasks such as PCB inspection benefit from segmentation models, whereas assembly verification requires contextual and temporal reasoning, which remains a challenge for standard object detection models. Overall, existing methods can be categorized based on their trade-offs between accuracy, speed, and robustness. Real-time industrial applications favor lightweight one-stage detectors, whereas high precision inspection tasks benefit from two-stage or hybrid models. However, current approaches remain limited in their ability to simultaneously handle low-latency constraints and complex assembly reasoning, highlighting a key gap for future research.

V. Discussion: Challenges and Solutions in Manufacturing CV

The adoption of CV in manufacturing continues to grow across applications such as anomaly detection, visual inspection, and quality control. Despite these advances, several challenges limit large-scale deployment. This section summarizes key challenges and emerging solutions in industrial CV systems.

a) Data Scarcity and Annotation: Limited availability of high quality annotated data remains a major constraint, particularly for DL models such as YOLO and R-CNN. Industrial datasets are difficult to collect due to privacy concerns, production constraints, and the rarity of defect or missing component cases.

To address this, synthetic data generation and transfer learning have been widely explored. GAN-based augmentation and simulation approaches improve dataset diversity and model performance [115]–[117], while transfer learning enables effective use of pretrained models in data limited settings [118]. Annotation cost is another bottleneck, requiring domain expertise and manual effort. Active learning reduces labeling requirements by selecting informative samples [119], while collaborative robotics and extended reality support efficient dataset creation [120], [121]. Despite these advances, challenges remain in annotation quality, dataset standardization, and scalability.

b) Scene Variability and Lighting: Manufacturing environments exhibit significant variability in lighting, object appearance, and background conditions, which affects detection robustness. Occlusions, reflections, and cluttered scenes further complicate inspection tasks.

Adaptive lighting strategies, including shape adaptive illumination using controllable light arrays, improve image quality and inspection reliability [122], [123]. These methods are particularly effective in applications involving reflective or complex surfaces, such as semiconductor inspection [124].

c) System Integration and Cost: Integrating CV systems into existing manufacturing infrastructure remains complex due to interoperability with hardware, software, and production systems [125]. High costs associated with specialized equipment and custom system design further limit adoption, especially for small and medium enterprises [126].

Cost effective solutions include the use of low cost hardware, open source frameworks, and transfer learning [126]. In addition, simulation based design and plug-and-play architectures improve scalability and facilitate deployment [127]. Ensuring system reliability under harsh industrial conditions remains a critical requirement.

d) Real-Time Processing: Real-time performance is essential in manufacturing environments with strict latency constraints [7]. In practical industrial systems, this is achieved through a structured CV pipeline comprising image acquisition, feature extraction, decision layers, and IoT/edge feedback loops, enabling closed-loop inspection and real-time process adaptation. One stage detectors are typically preferred due to lower inference time, while two stage models may not meet high throughput requirements. Edge computing addresses latency challenges by enabling on device processing and reducing reliance on cloud systems [35]. Recent implementations report inference latencies of 32-54 ms and end-to-end processing below 100 ms, suitable for industrial deployment. Edge enabled federated learning further improves model generalization across distributed sites while preserving data privacy [97]. However, balancing latency, accuracy, and energy efficiency remains an open challenge.

From an industrial validation perspective, practical deployment requires metrics beyond detection accuracy, including slot level recall, false accept rates, and production level defect rates (PPM). Continuous monitoring and MLOps frameworks are also important to ensure long-term reliability under changing manufacturing conditions.

e) Model Transparency and Trust: Deep learning models often lack interpretability, limiting trust in quality critical applications [128]. XAI addresses this by providing insights into model decisions, supporting validation and fault diagnosis [129], [130].

Techniques such as Grad-CAM provide visual explanations through saliency maps, while SHAP and LIME offer feature level and local model agnostic interpretations, respectively [34], [131]. These methods enhance traceability, support root-cause analysis, and improve compliance in industrial systems, particularly in high risk sectors [132], [133].

f) Quality Control and Predictive Maintenance: The integration of CV with IoT and AI enables proactive quality control and predictive maintenance, improving operational efficiency and reducing downtime. IoT facilitates real-time data exchange, while CV automates inspection and defect detection [134]–[138]. These systems support applications such as real-time monitoring and energy aware manufacturing [101], with ML improving robustness and classification performance [139]. However, Industrial IoT systems introduce challenges related to scalability, data integration, and real-time processing [140]. Overall, while CV technologies significantly enhance manufacturing processes, their effective deployment requires addressing challenges in data availability, system integration, real-time performance, and model transparency.

g) Industry Specific Validation Protocols:

VI. Conclusion and Industrial Outlook

CV has demonstrated strong potential for automated inspection in manufacturing; however, existing approaches involve trade-offs between accuracy, latency, and robustness. One-stage detectors enable real-time performance for high-throughput production but struggle with small objects and occlusions, while two-stage and hybrid methods improve localization at the cost of increased latency. Anomaly detection techniques generalize to unseen defects but lack the contextual reasoning required for reliable assembly verification.

Emerging paradigms, including Vision Transformers, multimodal RGB-D fusion, self-supervised learning, and edge intelligence, address these limitations, particularly in data-scarce and noisy environments. Nevertheless, challenges remain in data availability, real-time deployment, and system integration. In addition, explainable AI and human-in-the-loop frameworks are essential to ensure trust, traceability, and compliance in safety critical applications.

From a technology readiness perspective, CV approaches span multiple maturity levels. Established supervised deep learning systems have reached industrial deployment (TRL 7-9), whereas emerging paradigms such as transformers, multimodal perception, and federated learning remain at earlier stages (TRL 3-6) and require further validation. Bridging this gap will depend on improving scalability, robustness, and interoperability across production environments.

Overall, future progress will be driven by the convergence of edge intelligence, data efficient learning, and explainable AI. Achieving scalable and reliable missing object detection will require advances not only in algorithms but also in datasets, energy efficient deployment, and seamless integration within industrial workflows.

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