Review

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Review

A Survey on Machine Vision Techniques for Automated Quality Inspection in Industry

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Abstract

Automated quality inspection is a central component of modern industrial production processes. Over the past few decades, machine vision has evolved from rule-based, traditional image processing methods to data-driven machine learning and deep learning approaches. In particular, with the advent of powerful neural networks, significant progress has been made in the detection, classification, and localization of defects. At the same time, industrial applications place high demands on robustness, real-time capability, explainability, and the handling of rare or unknown defect patterns. This brief survey provides an overview of machine vision methods for industrial quality inspection. It systematizes classical image processing approaches, supervised, unsupervised, and semi-supervised learning methods, and discusses their strengths and limitations in real-world production environments. Furthermore, it examines multisensory and three-dimensional inspection approaches, aspects of industrial implementation, and current developments in the field of explainable artificial intelligence. Finally, this brief overview identifies outstanding challenges and research gaps and outlines future trends in automated quality inspection.

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1. Introduction

Ensuring consistently high product quality is a critical competitive factor in industrial manufacturing. Defective products not only lead to increased costs due to scrap and rework, but can also pose safety risks and damage a company's reputation. For this reason, automated quality inspection has become an integral part of modern production lines. Machine vision systems enable non-contact, objective, and reproducible inspection of components and products. Earlier industrial inspection systems were primarily based on traditional image processing methods, in which defects were identified using manually developed features, thresholds, and heuristic rules. These approaches are effective in controlled environments but reach their limits when dealing with complex surface structures, variable lighting, or high product variability. With the increasing use of machine learning and, in particular, deep learning, the paradigm of quality inspection has fundamentally changed. Learning-based methods allow relevant features to be automatically extracted from large amounts of data and complex defect patterns to be modeled. Nevertheless, the practical application of such methods remains challenging, as industrial datasets are often unbalanced, defects occur rarely, and new defect patterns only emerge during ongoing operation.

The aim of this survey is to provide a structured overview of existing machine vision methods for industrial quality inspection. It not only compares algorithmic approaches but also discusses their suitability for real-world production conditions. The focus is particularly on determining which methods are suitable for different inspection tasks and which outstanding challenges future research must address.

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2. Classic Processing Methods

Classic image processing methods [1–8] form the basis of many early industrial quality inspection systems and are still used in numerous applications today. These approaches are generally based on explicitly defined rules, handcrafted features, and deterministic decision-making processes. Their main advantages lie in their low computational complexity, high interpretability, and relatively simple implementation in real-time systems.

2.1. Feature Extraction

A central element [9–11] of classical inspection systems is the preprocessing of image data. This includes steps such as noise reduction, contrast adjustment, normalization, and geometric corrections. The goal of these methods is to minimize disruptive influences and highlight relevant structures in the image.

The actual defect detection is often based on manually developed features. These include geometric features such as edges, contours, or shapes, statistical texture features, and frequency-based approaches. Methods for edge detection, such as those using gradient operators, are particularly widespread, as many defects occur as local discontinuities on surfaces.

2.2. Segmentation

Feature extraction is often followed by image segmentation [12], in which relevant image regions are separated from the background. Classic segmentation methods include thresholding, region-based methods, and morphological operations. In industrial practice, thresholding methods are preferred because they are easy to implement and can be executed efficiently, provided the image conditions are sufficiently stable.

The actual determination of whether a defect is present is typically made by rule-based classifiers. These rules are often defined manually by experts and are based on thresholds or logical combinations of multiple features. Such systems are transparent and easy to understand, but require extensive manual adjustments when the product or environmental conditions change.

Table 1. Overview of classical image processing methods.

Year	Approach / Topic	Brief Description	Source
1987	Morphological operations	Noise removal and structuring	Haralick, R. M., et al. [13]
1986	Edge-based Segmentation	Edge detection for object separation	Canny, J. A [14]
2007	Adaptive Thresholding	Local thresholds for inhomogeneous images	Bradley, D. and Roth, G. [?]
1979	Otsu Method	Automatic global threshold selection	Otsu, N. A [?]
2005	Expert Systems	Rule-based defect detection	Liao, S. H. [?]
2004	Threshold Optimization	Comparison and evaluation of thresholding methods	Sezgin, M. and Sankur, B. [?]
1985	Connected Components	Identification of individual objects	Suzuki, S. and Abe, K. [15]

2.3. Applications and Limitations of Traditional Methods

Traditional image processing methods have proven particularly effective in applications with low product variability and clearly defined defects, such as dimensional inspection, presence detection, or the inspection of simple surfaces [16]. However, in highly dynamic production environments with variable lighting, complex textures, or subtle defect patterns, these approaches reach their limits.

A major disadvantage of classical methods is their low robustness against variations not explicitly accounted for in the rules. Furthermore, the development effort is high, as specific features and decision rules must be designed for each new inspection task [17]. These limitations have contributed significantly to the development and increasing prevalence of learning-based methods, which will be discussed in the next chapter.

3. Supervised Approches

With the growing success of deep neural networks in general image processing, supervised deep learning methods have also become increasingly important in industrial quality inspection. Unlike traditional approaches, these methods do not rely on manually defined features but instead learn

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relevant representations directly from annotated image data. This enables even complex defect patterns that are difficult to describe formally to be reliably detected.

3.1. Classification

Convolutional Neural Networks (CNNs) form the basis of many modern inspection systems. In its simplest form, quality inspection is formulated as a classification problem in which an image or a section of an image is classified as defect-free or defective. Such approaches are particularly suitable when defects are clearly visible and differ from the normal state on a global scale.

CNN-based classification models are characterized by high accuracy and good generalization ability, provided that sufficient training data is available. In industrial practice, however, this is often not the case, as defective parts occur rarely and manual annotation is time-consuming and costly. This leads to highly imbalanced datasets, which complicate the training of supervised learning models.

Zhang et al. [18] illustrate the effectiveness of CNNs for real-time surface quality inspection of additively manufactured (AM) metal parts. Their deep CNN classification model recognizes "beautiful-weld" categories with 100 percent accuracy using full images and ensemble outputs, demonstrating how deep learning can mitigate inefficiencies and errors associated with manual inspection. Building on this focus on robust, accurate classification, Semitela et al. [19] develop a dual-modal CNN system for automated defect detection. By comparing a custom-built CNN with transfer learning approaches (ResNet-50 and Inception V3), they achieve fast and accurate surface classification suitable for industrial deployment, highlighting the advantage of combining multiple illumination modes for improved model reliability. Singh and Desai [20] extend this concept by introducing a hybrid framework that integrates a pre-trained ResNet-101 CNN with a multi-class Support Vector Machine classifier for surface defect detection. Applied to the centerless grinding of tapered rollers, this approach addresses the constraints of limited datasets and computational resources, making deep learning accessible for MSMEs and SMEs. Similarly addressing practical industrial requirements, Riedel et al. [21] present the VIG Damage Classification Network (VDCNet), based on ResNet, for classifying damage in Vacuum Insulated Glazing units. The model demonstrates superior convergence speed, accuracy, precision, and ROC AUC, using microscope images to automate a critical quality control step. Islam et al. [22] provide an overview of CNN applications in supervised learning for industrial inspection, emphasizing variants such as ResNet and DenseNet. They highlight real-time evaluation of narrow overlap weld quality and introduce lightweight tailored networks such as PCBNet, Mobile-Unet, and VLSTM-integrated CNNs for electronics and textile manufacturing. These approaches exemplify how CNN architectures can be adapted to both material-specific inspection and computational constraints. Cui et al. [23] further demonstrate the potential of CNNs for classifying metal AM parts into good quality, crack, gas porosity, or lack of fusion. Using optical microscope images from the Missouri S&T dataset, the model achieves an average classification accuracy of 92.1 percent with 8.01 milliseconds recognition time per image, underscoring feasibility for real-time industrial inspection. Weiher et al. [24] expand on these principles by deploying state-of-the-art CNNs to classify infrared images of thermally conductive components in a factory setting, integrating dataset preparation, model training, and inline application. Transfer learning reduces dataset size requirements while maintaining high classification performance. Finally, Kovilpillai et al. [25] demonstrate the robustness of supervised CNN-based machine vision for detecting and classifying defective cement and ceramic tiles on an assembly line. Trained on 30,000 real-time images, the system achieves 99.96 percent accuracy, highlighting the scalability and reliability of CNN approaches across diverse industrial applications.

3.2. Detection and Segmentation

Detection and segmentation approaches are increasingly being used not only to identify defects but also to locate them spatially. Object detection models enable the localization of individual defect regions using bounding boxes, while segmentation models provide pixel-accurate delineation of defective areas.

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Segmentation-based approaches are particularly relevant for applications where the size, shape, or extent of a defect is critical, such as cracks, pores, or surface irregularities. However, as the required level of detail increases, so does the effort required to annotate the training data, which limits their industrial scalability.

Tabernik et al. [26] present a segmentation-based deep learning architecture specifically for surface anomalies, demonstrating superior performance in surface-crack detection. Notably, the approach requires only 25–30 defective samples, making it practical for industries with limited annotated data. Building on the idea of efficient defect localization, Ashourpour et al. [27] implement YOLOv8 for real-time detection of assembly defects and missing parts. Their study highlights high mean average precision (mAP) and shows that YOLOv8 can handle both object detection and segmentation, supporting in-line quality assurance. Similarly, Chen et al. [28] apply the YOLACT algorithm to detect and segment surface defects on metal screw heads. By combining automated microscopic scanning with high-speed processing (30 frames per second), the approach demonstrates real-time inspection capabilities, further illustrating the industrial relevance of integrating detection and segmentation. Extending this focus on pixel-level segmentation, Yang et al. [29] propose an encoder-decoder network designed to handle weak textures, low contrast, and class imbalance, using a residual attention backbone and bidirectional convolutional LSTM to capture long-range spatial context. While some approaches prioritize high-resolution pixel segmentation, others integrate precision measurement with traditional machine vision. Moru and Borro [30] develop Vision2D, a subpixel-precision system for industrial gear inspection, combining thresholding and edge-based segmentation with calibration via a Coordinate Measuring Machine. This bridges deep learning with conventional vision methods to achieve highly accurate defect detection. Complementing this idea, Chiou [31] presents an intelligent framework for selecting the most appropriate segmentation method based on the detected flaw type. Applied to 1,676 defective images across multiple industries, it reduces misclassification from 44 percent to 13.96 percent, showing that adaptive method selection can significantly improve inspection reliability. For more complex defect contexts, particularly welding or X-ray imaging, Yang et al. [32] introduce an attention-guided segmentation network with a U-shaped encoder-decoder architecture. By integrating a multiscale feature fusion block and bidirectional convolutional LSTM, the method enhances microdefect segmentation under challenging conditions such as low contrast and complex backgrounds. Similarly, Tsai et al. [33] use a two-stage scheme, combining CycleGAN-based defect synthesis with U-Net segmentation, allowing pixel-wise defect detection on textured surfaces without manual annotation. This approach demonstrates flexibility across varied materials, from machined metal to natural wood and medical patches. Other studies focus on real-time industrial deployment. Ozdemir and Koc [34] implement a smart factory system where a two-stage process—initial detection via an ANN and ACF object detector, followed by CNN classification which automatically separates not okay products on an assembly line. Extending these practical applications, Ahmed et al. [35] present a real-time object identification system using IoU refinement, Feature Pyramid Networks, and Region Proposal Networks. Compared to six conventional methods, their approach consistently achieves higher accuracy, speed, and adaptability, overcoming the traditional limitations of manual inspection and human error.

4. Unsupervised and Semi-Supervised Approaches

Unsupervised and semi-supervised learning methods have gained significant importance in recent years, as they address key challenges in industrial quality inspection. In particular, the lack of annotated defect data and the occurrence of previously unknown defect patterns make fully supervised approaches impractical in many real-world scenarios. Unsupervised methods aim to learn a model of the normal state and identify deviations from it as potential defects.

4.1. Anomaly Detection

Most unsupervised inspection systems follow the principle of anomaly detection. In this approach, the model is trained exclusively or predominantly on defect-free examples. During operation, deviations from the learned normal distribution are interpreted as anomalies. This paradigm is particularly

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attractive for industrial applications, as defect-free data is generally readily available, while defects occur rarely and in diverse forms.

A key challenge is to find a representation that describes the steady state with sufficient accuracy without learning trivial solutions in which defects are also correctly reconstructed or ignored.

Early and general approaches to anomaly detection demonstrate how this paradigm can be applied across different industrial domains. For instance, Wang et al. [36] introduce an unsupervised segmentation method combining feature learning, self-attention, and clustering to detect defects on additively manufactured surfaces using only a single scanned image. Their experiments across different materials and process parameters demonstrate robust performance, highlighting the potential for quality control without large labeled datasets.

Similarly, Lehr et al. [37] propose a two-step unsupervised approach for anomaly detection and defect clustering. By interpreting deviations from a dataset of defect-free samples as anomalies, the method avoids explicit defect learning and effectively detects defects on rigid bodies with highly non-uniform textures, extending anomaly detection beyond uniform surface inspection scenarios.

4.2. Autoencoder

Autoencoders are among the most commonly used unsupervised models in quality inspection. They consist of an encoder, which projects the input image into a latent space, and a decoder, which attempts to reconstruct the original image. During training on defect-free data, the model learns to map typical structures of the normal state.

Defects are typically identified based on a reconstruction error. Areas that cannot be reconstructed well are interpreted as anomalous. Extensions such as variational autoencoders enable probabilistic modeling of the latent space and, in some cases, improve the separation between normal and defective patterns.

Autoencoder-based approaches are relatively easy to implement and can be trained efficiently. However, their performance depends heavily on whether the model actually learns to ignore defects or whether it unintentionally reconstructs them as well.

Several studies demonstrate the applicability of autoencoder-based anomaly detection in different industrial contexts. Choi and Kim [38] extend unsupervised learning to Industrial Control Systems (ICSs), using a composite autoencoder to detect and classify anomalies without pre-labeled data. Validated on HIL-augmented datasets, the method accurately identifies anomalous patterns in both value and time dimensions, addressing the challenges of complex industrial environments.

Extending this concept to machinery condition monitoring, Ahmed et al. [39] propose a six-layer autoencoder framework for anomaly detection in wind turbine components. By incorporating vibrational analysis to assess defect severity, the framework achieves 91 percent overall accuracy, enabling proactive fault diagnosis and maintenance decisions.

4.3. GAN-Based Anomaly Detection

Generative Adversarial Networks have also been successfully used for unsupervised defect detection. In this context, a generator learns to produce realistic images of the normal state, while a discriminator distinguishes between real and generated images. Deviations from the learned normal image can be used as an indicator of defects.

GAN-based methods often enable sharper reconstructions than classical autoencoders, but they are more difficult to train and more prone to instability. Furthermore, the interpretation of anomaly scores is often less intuitive, which can limit their industrial acceptance.

In addition to reconstruction-based approaches, segmentation-oriented architectures have also been explored in unsupervised settings. Cao et al. [40] propose a pixel-level encoder–decoder segmentation network with deep feature fusion. Their multilevel feature aggregation module captures both contextual information and fine defect details, while a multibranch decoder with attention progressively reconstructs defect structures, achieving high performance on public datasets such as MT, RSDD, and CFD.

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4.4. Semi-Supervised Methods

Semi-supervised approaches extend unsupervised models by incorporating a limited amount of annotated defect data. This additional information can be used to refine decision boundaries or to specifically account for certain defect types. In practice, semi-supervised methods often represent a good compromise between data requirements and performance.

Extending the previous unsupervised strategies, semi-supervised approaches incorporate some annotated defect data to refine detection and segmentation results.

Zhang, Pan, and Zhang [41] develop a semi-supervised generative adversarial network (SSGAN) with two sub-networks for pixel-level defect segmentation. By incorporating unlabeled images, the model enhances segmentation quality and reduces reliance on extensive labeling. Tested on a public dataset of four steel defect classes, the SSGAN achieves promising mean Intersection over Union (IoU) scores while using only a fraction of labeled data compared to state-of-the-art supervised methods. Shi et al. [42] extend semi-supervised segmentation with a framework combining perturbation invariance and diverse perturbation cross-pseudo-supervision. By integrating edge pixel-level information and shallow feature fusion into a lightweight architecture, the method improves real-time performance, edge detection, and small target segmentation. Evaluated on both a private industrial dataset and the public KolektorSDD dataset, the approach achieves higher mean IoU than existing semi-supervised methods. Similarly, Mannivannan [43] focuses on additive manufacturing, proposing a semi-supervised deep learning system for real-time monitoring of selective laser sintering (SLS) powder bed defects. Trained with both labeled and unlabeled data, it attains state-of-the-art accuracy on multiple defect inspection datasets, including NEU steel surface defects and KolektorSDD, while significantly reducing manual labeling effort. Yang, Wu, and Feng [44] introduce MemSeg, an end-to-end memory-based network for high-accuracy, real-time semi-supervised surface defect detection. By combining artificially simulated abnormal samples with memory samples of normal patterns, the network explicitly learns the distinction between normal and defective images. MemSeg achieves state-of-the-art performance on MVTec AD datasets for defect detection and localization, while meeting industrial real-time processing requirements.

5. 3D and Multisensory Approaches

While many industrial inspection systems rely exclusively on two-dimensional image data, multisensory and three-dimensional approaches are becoming increasingly important. The use of additional sensor modalities extends inspection capabilities beyond purely visual information [45]. Two-dimensional image processing often reaches its limits, particularly in geometric inspection tasks. Height differences, volume deviations, or shape defects can frequently only be detected indirectly or unreliably in 2D images. 3D sensors provide explicit depth information, allowing for a more precise analysis of the geometric structure of components. Typical applications include dimensional inspection, flatness checks, deformation detection, and the inspection of complex free-form surfaces. 3D inspection systems are particularly widespread in the automotive, electronics, and plastics industries.

5.1. 3D Capture

Three-dimensional inspection begins with the capture of 3D data using various sensor technologies such as structured light systems, stereo cameras, time-of-flight sensors, and laser triangulation. Each technology offers specific advantages and trade-offs in terms of resolution, measurement accuracy, speed, and robustness against environmental influences. The choice of sensor depends heavily on the requirements of the inspection task: high-resolution systems allow detailed surface analysis but are often more expensive and computationally intensive, whereas faster sensors are better suited for high-speed production lines but usually provide lower depth resolution. Once captured, 3D data is processed and analyzed using approaches that differ fundamentally from traditional 2D image processing. Point clouds, depth images, or elevation maps are typically analyzed through geometric features, distance measurements, or direct comparisons with CAD reference models. Learning-based

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methods using deep learning have also been developed, allowing models to extract relevant geometric patterns directly from raw 3D data. These approaches can improve inspection performance but require high computational resources and suitable training datasets, which are often more challenging to obtain than in 2D cases.

5.2. Multisensory Data Fusion

A promising approach involves combining multiple sensor modalities, such as RGB images with depth information or multispectral data. By fusing different data sources, both visual and geometric or material-dependent properties can be taken into account.

Multisensory systems demonstrate greater robustness against failures of individual sensors and enable more accurate fault detection. At the same time, however, system complexity increases, both in terms of hardware integration and in terms of data processing and modeling.

These approaches have been increasingly adopted in research and industrial applications, with recent studies demonstrating their effectiveness in various multisensory and 3D inspection scenarios.

Chen et al. [46] present a multisensor fusion-based digital twin for in-situ quality monitoring and defect correction in robotic laser-directed energy deposition, a type of additive manufacturing. By integrating acoustic sensors, infrared thermal cameras, coaxial vision cameras, and laser line scanners, the system performs 3D spatiotemporal data fusion to predict part quality and enable targeted defect correction across the 3D volume of the part. Building on the importance of multiple viewpoints, Kubieniec [47] highlights the role of advanced quality control platforms using two or more 3D scanners to capture sequential or parallel scans, automatically aligning and merging data into high-resolution 3D models. The inclusion of contact optical probes further improves measurement completeness for hard-to-reach areas, establishing 3D scanning as a cornerstone of modern quality control. Extending these principles to on-site applications, Kim et al. [48] propose a defect inspection system for building construction that fuses multiple RGB-D sensors with deep learning. Their three-step process—point cloud acquisition, deep learning-based registration, and defect inspection/visualization, facilitates detailed assessment of structural defects such as framework distortions or sagging floors and ceilings. Similarly, Dhabaseelan [49] employs a modular multi-camera inspection system for real-time monitoring in manufacturing, applying 3D point cloud processing and combining Local Surface Variation (LSV) with DBSCAN clustering to isolate defective points and verify dimensional quality. Singh [50] emphasizes the broader potential of multisensory AI in manufacturing. By fusing data from vision, LiDAR, acoustic, and tactile sensors, these systems provide a holistic understanding of production environments, enabling precise 3D reconstruction, spatial analysis, and reliable defect detection. Colosimo [51] demonstrates a complementary approach using Gaussian process models (kriging) to fuse point sets from multiple instruments for dimensional and geometric verification. His work shows that multisensor fusion can enhance metrological performance and identify potential sources of measurement error beyond the capabilities of single-sensor datasets. Finally, Muntean, Bocanet, and Fratila [52] introduce an AI-assisted framework to improve interpretation of complex 3D inspection results, such as CAD-vs-Mesh deviation reports. By integrating vision-language systems and large language models, the framework translates raw inspection data into context-rich, actionable narratives. A demonstrator on an automotive component illustrates how multisensor and AI-assisted analysis can generate detailed insights from high-volume 3D scanning data.

6. Industrial Implementation

In addition to pure recognition performance, the industrial applicability of machine vision systems poses a key challenge. Quality inspection systems must operate reliably, stably, and often in real time under real production conditions. This requires close integration of algorithms, hardware, and system architecture.

Industrial production environments are characterized by high throughput rates, limited cycle times, and strict reliability requirements. Inspection systems must make decisions within fixed time windows without disrupting the production flow. At the same time, misclassifications must occur only to a very limited extent, as both false positive and false negative decisions can incur significant costs.

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Furthermore, systems must be robust against fluctuations in lighting, vibrations, temperature, or material properties. These conditions place high demands on the stability and generalizability of the machine vision methods employed.

6.1. Hardware Platforms

The choice of hardware plays a crucial role in the real-time capability of inspection systems. Traditional image processing systems were often implemented on industrial PCs or programmable logic controllers (PLCs). With the advent of deep learning, high-performance GPUs and specialized accelerators are increasingly being used.

Edge computing platforms make it possible to run complex models directly near the production line, thereby reducing latency and better meeting data protection requirements. Alternatively, FPGA-based solutions offer high energy efficiency and deterministic runtimes, but require significant development effort.

Recent studies illustrate how these production line requirements are addressed in practice, demonstrating hardware and system designs capable of real-time, robust inspection under industrial conditions.

Frustaci et al. [53] implement a computer vision system for catalytic converter assembly under tight time and space constraints. By deploying the system on a Xilinx Zynq heterogeneous system-on-chip with hardware–software co-design and dedicated accelerators, they achieve a 23-fold speed-up over software-only implementations, enabling real-time inspection without affecting production. Similarly, Asad [54] demonstrates real-time defect detection with a multi-view multimodal fusion network (2M3DF) operating at 29.8 frames per second. By combining multi-view RGB images and 3D point clouds, the system addresses computational complexity and inference speed limitations in 3D industrial manufacturing defect detection. Bhandarkar [55] integrates Additive Manufacturing with Industry 4.0 concepts, remotely monitoring a delta 3D printer via a Raspberry Pi and Python sockets. A CNN-based machine vision component detects stringing defects in real-time with 99.31 percent accuracy, confirming suitability for low-latency, real-world 3D printing scenarios. Complementing these approaches, Chen et al. [46] develop a multisensor fusion-based digital twin for robotic laser-directed energy deposition, combining acoustic, vision, and thermal sensors to provide real-time feedback for online anomaly detection. The system predicts location-specific quality and enables on-the-fly material adjustments, facilitating self-adaptive cyber-physical production systems. Expanding real-time inspection to large-scale additive manufacturing, Martin et al. [56] propose a methodology using 2D LiDAR integrated directly into concrete printing machines. By continuously monitoring extrudate width and height with a Variable Standard Deviation (VSD) algorithm, the system detects defects promptly, preventing excessive layer deformations while achieving sub-millimeter accuracy. The integration into the machine itself eliminates the need for external inspection robots, demonstrating feasibility for outdoor and remote fabrication.

7. Explainability and Trust in AI-Based Inspection Systems

With the increasing prevalence of machine learning-based machine vision systems in industrial quality inspection, the issue of explainability is coming increasingly into focus. While traditional rule-based methods are easy to understand due to their transparent decision-making logic, deep learning models are often perceived as black-box systems. This lack of transparency represents a significant barrier to acceptance, particularly in industrial and safety-critical applications.

7.1. The Importance of Explainability in Industrial Applications

In industrial quality control, inspection systems serve not only to automate decision-making but also to support quality engineers and operating personnel. Decisions regarding rejects, rework, or process adjustments must be traceable and justifiable. Misclassifications without a discernible cause can permanently undermine trust in the system.

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Furthermore, explainable decisions are often a prerequisite for certifications, audits, and compliance with regulatory requirements. In this context, the ability to present model decisions transparently takes on central importance.

7.2. Visualization of Model Decisions

A common approach to improving explainability involves visualizing the image regions that contribute significantly to a model's decision. Such visualizations make it possible to verify whether the model actually takes defect-relevant structures into account or whether it reacts to irrelevant artifacts.

In quality inspection, such methods are frequently used to visually highlight detected defects and enable the user to intuitively interpret the decision. This is particularly advantageous for locally confined defects such as cracks, scratches, or inclusions.

7.3. Explainability in Unsupervised Methods

Explainability also plays an important role in unsupervised and semi-supervised approaches. Reconstruction-based methods offer an inherent advantage here, as the difference between the input image and the reconstruction can be interpreted as an indication of anomalous areas. Such difference images can be used directly as a visual explanation.

However, caution is also warranted with these methods, as not every deviation from the normal state necessarily represents a relevant defect. A clear interpretation of the anomaly scores and their visual representation is therefore crucial for practical application.

7.4. Trust, Human-AI Interaction, and Hybrid Systems

Explainable inspection systems not only foster trust in individual decisions but also support effective collaboration between humans and AI. In hybrid systems, AI models handle the pre-selection of potential defects, while human experts perform the final assessment.

Such human-AI interaction concepts make it possible to combine the strengths of both sides: the speed and consistency of automated systems, as well as the experience and contextual knowledge of human inspectors. Explainable outputs are a key prerequisite for efficient collaboration in this context.

Recent research has increasingly transferred these principles into practical industrial settings, demonstrating how explainable AI (XAI) methods can enhance trust, interpretability, and human–AI collaboration in quality inspection. Initial work in this direction focuses on integrating XAI directly into manufacturing processes. For instance, Goldmann et al. [57] demonstrate the application of XAI methods in manufacturing, enabling AI systems to automatically explain their reasoning and outputs. Applied to ultrasonic weld quality prediction and body-in-white dimensional variability reduction, their approach highlights the importance of explainability for fostering trust in industrial environments. Building on this, Bordekar et al. [58] extend the use of XAI to metal additive manufacturing, employing computed tomography scans to detect and characterize defects. By enhancing model transparency, their method allows AI-driven decisions to be explained and justified, which is particularly relevant for safety-critical applications. A complementary line of research emphasizes explainability in the context of measurement and multimodal analysis. Lavasa et al. [59] propose leveraging XAI to predict measurement accuracy in complex 3D scanning systems. Their use of visual 3D deviation maps provides intuitive insights into predicted versus actual deviations, thereby improving stakeholder understanding and trust in metrology AI. Similarly, Ahangar et al. [60] apply XAI techniques such as Grad-CAM and SHAP across both visual and acoustic domains, aligning model outputs with physically interpretable defect mechanisms and enabling transparent, auditable decision-making. Beyond individual applications, several studies investigate the broader role of XAI in human–machine interaction. Rovzanec et al. [61] show that explainability makes machine learning models more intelligible to human users, thereby forming a foundation for trust and effective collaboration in visual inspection tasks. In the same vein, Baek et al. [62] argue that insufficient transparency reduces manufacturers' confidence and limits process optimization. To address this, they propose transforming pixel-level attributions into object-level severity reasoning, quantified

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through a Quality Risk Score (QRS), enabling interpretable and scalable defect assessment. Finally, other contributions focus on the adoption and acceptance of AI systems in industrial practice. Kucher et al. [63] note that black-box models are often mistrusted when their outputs do not align with operational requirements, and propose XAI-driven visual analytics as a means to calibrate user trust and support decision-making. This perspective is reinforced by Aboulhosn et al. [64], who show that unfamiliarity with automated decisions can hinder the adoption of visual inspection systems. By employing XAI methods such as Grad-CAM, SHAP, and LIME, these approaches make deep learning models more transparent and accessible, thereby facilitating their integration into industrial workflows.

8. Outstanding Challenges and Research Gaps

Despite significant advances in machine vision for industrial quality inspection, several challenges remain that limit the widespread deployment of these systems. The development of deep learning–based systems for industrial quality inspection faces several interconnected challenges. Supervised models require large amounts of annotated defect data, which is often expensive or impractical to obtain. While unsupervised or semi-supervised approaches can reduce the need for labeled data, their performance still suffers when defect types are highly variable or rare. At the same time, models must operate reliably across diverse industrial environments, accounting for varying lighting conditions, surface textures, and material properties. Many applications also demand real-time operation, requiring careful optimization of hardware and software when using computationally intensive models or integrating multiple sensor data. Another critical aspect is the interpretability of decisions. Deep learning systems are often seen as black boxes, making explainable outputs necessary to ensure trust, compliance, and process auditing. Using multiple sensors, such as RGB, depth, thermal, acoustic, or LiDAR, can improve defect detection but adds complexity due to calibration, synchronization, and data fusion. Finally, detecting novel or rare defects remains an open challenge. While current anomaly detection and semi-supervised methods show promise, fully reliable detection in dynamic production environments has yet to be achieved.

Addressing these challenges is essential to move from laboratory research to robust, scalable, and industrial-grade machine vision systems. To contextualize these challenges, Table 2 provides a summary of the main machine vision methods used in industrial quality inspection, highlighting their typical techniques, data requirements, strengths, and limitations.

Table 2. Overview of Machine Vision Methods for Industrial Quality Inspection.

Method Class	Typical Techniques	Data Requirements	Strengths	Limitations
Classical Image Processing	Edge and texture analysis, thresholding, morphology	No annotation required	High interpretability, low computational load, real-time capable	Low robustness, high manual development effort
Supervised Deep Learning	CNN classification, object detection, segmentation	Large amounts of annotated defect data	High accuracy, complex defect patterns detectable	Data-intensive, limited to known defects
Unsupervised methods	Autoencoders, VAEs, GAN-based models	Predominantly error-free data	Detection of unknown defects, low labeling effort	Difficult threshold selection, reconstruction of defects
Semi-supervised methods	Combination of anomaly detection and classification	Few annotated defects + normal data	Good compromise between performance and data requirements	Model and training complexity
Feature-based anomaly detection	Pre-trained CNN features, statistical models	Only error-free data	Good generalization, stable performance	Dependence on pre-trained models
3D Inspection	Point cloud analysis, elevation maps, CAD comparison	3D data, often without annotations	Precise geometric inspection, robust shape analysis	High hardware and computational requirements
Multisensory Approaches	RGB-D, multispectral fusion	Multiple synchronized data sources	Increased robustness, more physical information	Complex integration, high system costs

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9. Conclusion and Outlook

This survey has presented an overview of machine vision techniques for automated quality inspection in industrial settings, covering classical image processing, supervised deep learning, unsupervised and semi-supervised methods, as well as 3D and multisensory approaches. Each class of methods offers unique advantages: classical techniques provide interpretability and simplicity, supervised learning delivers high accuracy for known defect types, and unsupervised approaches enable detection of unknown anomalies with minimal labeling effort. Multisensory and 3D methods further extend inspection capabilities by capturing geometric and material properties that are not visible in standard 2D images. Looking forward, the combination of robust deep learning models, efficient real-time implementations, and explainable outputs will be key to fully automated, trusted, and scalable industrial quality inspection. Future research should focus on reducing data dependency, improving generalization across variable production conditions, integrating multisensory systems, and enhancing human-AI collaboration through transparent decision-making. By addressing these challenges, machine vision has the potential to significantly increase production quality, reduce waste, and accelerate the adoption of intelligent manufacturing systems.

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