Advancements in Machine Vision Systems for Automated Quality Control in Manufacturing

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ABSTRACT

Machine vision systems have revolutionized quality control in manufacturing by offering automated, precise, and real-time defect detection. These systems integrate AI and deep learning for enhanced accuracy and adaptability, significantly improving production efficiency across industries such as automotive, electronics, and aerospace. Recent innovations include automated defect detection through image processing algorithms, AI-based frameworks for anomaly detection, and integration with industrial automation systems like PLCs. While large-scale adoption faces challenges, such as high costs and lack of technical expertise, the evolution of machine vision continues to shape smart manufacturing environments, improving both operational and inspection accuracy.

Keywords: *Machine Vision, AI, Manufacturing, Defect Detection, Industrial Automation.*

I. INTRODUCTION

In modern manufacturing industries, maintaining high product quality, reducing defects, and ensuring consistent production efficiency have become critical priorities due to increasing global competition and the rapid evolution of Industry 4.0 technologies. Traditional manual inspection methods, although widely used, are often time-consuming, subjective, and prone to human error. As a result, there has been a significant shift toward automated quality inspection systems based on machine vision techniques, which offer higher accuracy, repeatability, and real-time decision-making capabilities (Xiao et al., 2023; Silva & Paladini, 2025). Machine vision systems utilize imaging sensors, cameras, and advanced image processing algorithms to inspect products, detect defects, and ensure compliance with predefined quality standards. These systems are increasingly integrated with artificial intelligence (AI), deep learning, and industrial automation frameworks, making them a core component of smart manufacturing environments. The growing demand for precision manufacturing in sectors such as automotive, electronics, aerospace, and medical devices has further accelerated the adoption of machine vision-based inspection systems (Werheid et al., 2025). Recent research highlights the evolution of machine vision from conventional rule-based inspection toward intelligent, AI-driven systems capable of learning from data and adapting to complex industrial conditions. For instance, Gao et al. (2026) emphasized the transformation of magnetic particle inspection (MPI) from manual visual assessment to intelligent inspection systems supported by automation control and advanced image analysis. Their study demonstrated how critical parameters such as magnetic field strength and powder characteristics influence defect detection, while also identifying key subsystems including image acquisition, processing, and spatial positioning for intelligent inspection development. Similarly, Nasril et al. (2026) demonstrated the integration of machine learning techniques, specifically Support Vector Regression (SVR), with sensor-based measurement systems for real-time anomaly detection in manufacturing processes. Their findings highlighted that non-contact laser probing combined with intelligent algorithms achieved up to 99% accuracy in defect detection, reinforcing the effectiveness of data-driven inspection systems in Industry 4.0 environments. The integration of machine vision with programmable logic controllers (PLCs) has further enhanced industrial automation capabilities. Maślanka et al. (2025) presented a vision-PLC integrated system using Cognex smart cameras and Allen-Bradley PLCs, achieving detection accuracy above 95% and reducing false classifications significantly. Their work emphasized real-time synchronization, deterministic communication, and industrial scalability, although challenges such as lighting sensitivity and limited dataset availability were identified.

In small and medium-sized enterprises (SMEs), Werheid et al. (2025) reported that machine vision adoption is growing but remains constrained by financial limitations, lack of technical expertise, and insufficient training data. Despite these barriers, machine vision is increasingly used for quality control, classification, and defect detection, with low-cost hardware and open-source software emerging as viable solutions. In electronics manufacturing, Silva et al. (2025) developed a hybrid smart vision system for PCB inspection, demonstrating high accuracy in detecting surface-mounted components and improving decision-making in assembly lines. Likewise, Yang et al. (2025) introduced an augmented reality (AR)-assisted machine vision inspection system that improved human–machine interaction and defect visualization, showing superior performance compared to traditional inspection methods. Further advancements in AI-based inspection systems have been reported by Xiao et al. (2023), who developed a deep learning-based detection framework for early defect identification in manufacturing lines. Their system enabled early-stage quality control, reducing defective product propagation and improving production efficiency. Park and Jeong (2022) also demonstrated the successful application of deep learning and machine vision in mask manufacturing during the COVID-19 pandemic, highlighting improved defect detection and process monitoring capabilities. On-machine inspection systems have also gained attention in modern manufacturing environments. Taatali et al. (2024) proposed a CNC-based vision inspection system using point cloud analysis and remapping algorithms for dimensional inspection, achieving improved automation and accuracy in production lines. Similarly, Rajan et al. (2021) developed a CNN-based bolt inspection system using Raspberry Pi, demonstrating the effectiveness of embedded vision systems for real-time defect detection. At the foundational level, Moru and Borro (2020) introduced a machine vision algorithm for gear inspection with subpixel accuracy, achieving high calibration precision and demonstrating strong agreement with coordinate measuring machine (CMM) validation results. Their study reinforced the importance of high-resolution imaging and algorithmic precision in industrial inspection applications. Collectively, these studies indicate a clear technological progression from traditional inspection systems to fully automated, intelligent machine vision frameworks. The integration of AI, deep learning, sensor technologies, and industrial control systems has significantly enhanced inspection accuracy, operational efficiency, and scalability. However, challenges such as dataset limitations, environmental sensitivity, integration complexity, and high implementation costs still persist, particularly in SMEs and large-scale production environments.

II. RESEARCH BACKGROUND

Gao et al. (2026) reviewed magnetic particle inspection (MPI) as a classical non-destructive testing method and reported that it had occupied a significant position in industrial applications because of its simplicity, cost-effectiveness, and reliability. The authors explained that, with the advancement of intelligent technologies, MPI had gradually evolved from traditional manual visual inspection toward high-precision intelligent inspection systems through the integration of automation control and intelligent analysis algorithms. Their study systematically examined the prevailing industrial status of MPI and analyzed the major factors influencing defect display, including magnetic field strength, magnetization current, magnetization method, and magnetic powder performance. They further discussed the developmental trajectory of intelligent MPI by focusing on three essential components, namely image acquisition systems, image processing systems, and spatial positioning systems. The review also identified persistent challenges in achieving fully intelligent MPI and suggested future directions aimed at improving automation levels and optimizing inspection accuracy.

Nasril et al. (2026) examined the importance of measurement systems and sensor technologies in production engineering within advanced manufacturing environments. The authors reported that on-machine measurement systems had enabled real-time evaluation and anomaly detection for effective product quality monitoring, machining parameter assessment, operational condition tracking, and outcome verification directly on machine tools. The study presented an anomaly detection framework based on Support Vector Regression (SVR) to improve monitoring performance in automated manufacturing systems. It was noted that the framework utilized small- to medium-dimensional sensor data obtained through laser-based non-contact probing techniques. The findings indicated that the SVR model had achieved an impressive anomaly detection accuracy of 99%, demonstrating strong predictive capability. Furthermore, the authors highlighted that the proposed model had successfully captured complex nonlinear patterns and adapted efficiently to diverse abnormal operating conditions. Overall, the study concluded that the SVR-based framework had offered a practical, intelligent, and reliable solution for real-time production monitoring in the context of Industry 4.0.

Maślanka et al., (2025) examined the growing importance of integrating machine vision systems with programmable logic controllers (PLCs) for automated quality assurance in Industry 4.0 environments. They presented an applied case study of vision–PLC integration, with emphasis on real-time synchronization, deterministic communication, and practical industrial deployment. The study employed a Cognex In-Sight 2802C smart camera integrated with an Allen-Bradley Compact GuardLogix PLC through Ethernet/IP implicit cyclic exchange. Three representative case studies were investigated, including 3D-printed prototypes with controlled defects, automotive electrical connectors inspected using Cognex ViDi supervised learning tools, and fiber optic tubes evaluated through a custom fixture-based heuristic method. The findings indicated that detection accuracy had exceeded 95%, while PLC-level triple verification had reduced false classifications by 28% compared to camera-only operation. The authors highlighted improved robustness, real-time performance, and dynamic tolerance adjustment, while also noting limitations such as lighting sensitivity, small datasets, and scalability challenges in full production environments.

Werheid et al. (2025) conducted a systematic literature review on the adoption of machine vision systems in industrial small- and medium-sized enterprises (SMEs). The authors observed that machine vision had increasingly been used to automate manufacturing tasks such as quality control, fault detection, part classification, and inventory management, thereby improving efficiency, accuracy, and productivity. They reported that the growth of the machine vision market had been strongly driven by manufacturing applications in both hardware and software domains. However, the study highlighted that SMEs had faced considerable human, technical, and organizational barriers in implementing such systems. Based on an analysis of 770 articles, the review identified quality control as the most prominent application area. It was further noted that limited investment capacity, shortages of skilled labor and expertise, and high-variety, low-volume production had been major constraints, often resulting in insufficient training data. The authors suggested that low-cost hardware, open-source software, and user-friendly systems had emerged as practical solutions, while broader interdisciplinary approaches remained limited.

Silva et al. (2025) reported that rapid technological advancements in printed circuit board (PCB) production had increased the number of surface-mounted components, which had created a growing need for improved inspection processes in the electronics industry. They observed that this trend had encouraged higher levels of automation in production lines, particularly through the use of machine vision for quality inspection and decision-making regarding product acceptance or rejection. The study had proposed a hybrid smart-vision inspection system that integrated machine vision concepts with vision sensor equipment to inspect 24 components and eight screw threads in automotive assembly fixtures. It was stated that the system had utilized a camera for capturing real-time images linked to a CMOS color vision sensor. The findings had demonstrated high accuracy, feasibility, and effectiveness in complex industrial environments. The study further concluded that the Vision Builder-based automated inspection strategy had enhanced inspection performance, reduced non-conformity rates, and improved action priority through better failure mode and effect analysis (FMEA).

Yang et al. (2025) examined the importance of rapid feedback, accurate inspection outcomes, and human-centered intuitive visualization during industrial inspection activities. They proposed a SAR- and machine vision-assisted inspection (SARMVI) approach that utilized projector-based augmented reality and deep learning-based line detection to enhance system performance and reliability. In their study, the evaluation of gap spacing was carried out using the Mobile Line Segment Detection (MLSD) algorithm, which enabled robust and efficient visualization through virtual-real fusion. The authors compared the traditional Feeler Gauge-assisted Inspection (FGI), the screen-based machine vision inspection (SMVI), and the proposed SARMVI method through a case study involving different interactive interfaces. Their experimental findings indicated that the SARMVI approach significantly improved inspection performance, precision, and visual perception experience when compared with SMVI. They further reported that both SMVI and SARMVI were effective and promising for industrial inspection applications. However, they also acknowledged certain limitations, including the requirement of planar surfaces and the need for manual light adjustment across varying environments.

Taatali et al. (2024) examined the transformative role of artificial intelligence in modern industrial systems and observed that its integration had significantly enhanced automation, productivity, and operational efficiency. They noted that achieving advanced automation remained challenging in sensitive applications such as manufacturing inspection, where precision and consistency were essential for in-line production. The authors proposed a systematic machine vision-based approach for on-machine inspection to automate and improve the inspection of CNC-machined parts. Their method incorporated a remapping algorithm along with image processing techniques to accurately extract required features, which were then subjected to dimensional inspection through generated point clouds. Experimental testing was carried out on a sample component using a CMOS camera mounted on the spindle of a 5-axis CNC machining center. The study further explored multiple stages of the proposed framework and emphasized critical factors necessary for well-structured experimentation. The findings reportedly demonstrated promising results, highlighting the method’s potential to strengthen industrial automation and improve manufacturing efficiency across production lines.

Xiao et al. (2023, November) reported that, with the increasing maturity of deep learning, machine vision systems integrated with AI-based deep learning algorithms had been widely applied in industrial settings. They explained that the proposed AI-based intelligent detection system had been designed to provide early warnings for preventing defective products during manufacturing. It was observed that quality assurance testing could be conducted at the early stages of production, thereby reducing the possibility of defective components entering subsequent processes. The authors highlighted that, in comparison with traditional manual inspection methods, AI-based machine vision detection had offered greater efficiency and improved accuracy. They also noted that the system had enabled the collection of detailed defect information and visual drawings of faulty products for further analysis and decision-making. Overall, the study had aimed to propose an AI-based machine vision detection system that could serve as a useful reference for intelligent quality inspection and defect detection in washing machine manufacturing processes.

Park and Jeong (2022) examined the application of deep learning and machine vision for anomaly detection in the mask manufacturing process during the COVID-19 period. They noted that, although advanced technologies such as machine vision, machine learning, and deep learning had already been widely introduced in manufacturing, their design and implementation in mask production sites had remained largely unexplored. The study was conducted with the aim of improving sustainable productivity and promoting industrial sustainability in pandemic-related manufacturing environments. The authors specifically described the construction and implementation procedures of hardware and software systems for quality inspection automation, process control automation, POP manufacturing monitoring, and smart factory solutions. The research was presented as a qualitative application study carried out in an actual Korean mask manufacturing company, referred to as "Company A." It was reported that a deep learning and machine vision-based anomaly detection system was implemented using the LAON PEOPLE NAVI AI Toolkit, which significantly improved defect detection productivity and was expected to support sustainability in similar manufacturing facilities.

Rajan et al. (2021) reported that the inspection of bolts had been difficult under conventional quality checking procedures, particularly in ensuring interchangeability and accurate defect detection. They observed that computer vision-based inspection had emerged as a suitable and efficient method for identifying defects in mechanical components within industrial applications. The study had aimed to develop a device for detecting bolt defects by using computer vision technology integrated with image processing techniques. The authors had focused on the development of a vision-based measurement and inspection system in which a camera had been combined with algorithms for automated defect recognition. The proposed work had mainly been based on a self-learning convolutional neural network (CNN) to enhance defect detection accuracy. The algorithm had been developed in the C programming language and repeatedly tested for reliability. It had then been implemented on a Raspberry Pi board, where a neural stick and camera had been attached to capture images, analyze them, and identify bolt defects effectively.

Moru and Borro (2020) reported that quality control had become a major priority in industrial gear inspection due to technological advancement and the emergence of Industry 4.0, where smart factories required highly precise and accurate measurement systems. The authors explained that machine vision technology had offered an image-based solution for gear inspection by integrating software, sensors, cameras, and robotic guidance. Their study had aimed to develop an improved machine vision application, namely Vision2D, for subpixel-level measurement and inspection of industrial gears in order to enhance quality control, reduce downtime, and optimize inspection efficiency. It was observed that the system had achieved a very low calibration error of 0.06 pixels. The calibrated system had then been validated against a Coordinate Measuring Machine (CMM) using the outer diameter of a reference gear. Furthermore, twelve additional gear samples had been examined under a tolerance limit of ±0.020 mm, where eight gears had been accepted and four had been rejected. The findings had demonstrated improved algorithmic performance over previous inspection methods.

III. KEY FINDINGS FROM STUDY

Author (Year)	Methodology	Key Focus	Findings
Gao et al. (2026)	Review of MPI with intelligent imaging systems	Magnetic particle inspection evolution	Shift toward AI-based intelligent MPI with improved defect detection
Nasril et al. (2026)	SVR-based anomaly detection using sensors	Real-time quality monitoring	99% accuracy in anomaly detection
Maślanka et al. (2025)	Vision + PLC integration	Industrial automation inspection	>95% accuracy, reduced false detection
Werheid et al. (2025)	Systematic literature review	Machine vision in SMEs	High adoption but limited by cost and expertise
Silva et al. (2025)	Hybrid vision system for PCB inspection	Electronics assembly inspection	High accuracy, improved decision-making
Yang et al. (2025)	AR + machine vision system	Human-centered inspection	Improved visualization and inspection precision
Taatali et al. (2024)	CNC on-machine vision system	Dimensional inspection	Enhanced automation and accuracy
Xiao et al. (2023)	Deep learning-based system	Early defect detection	Improved efficiency and reduced defect propagation
Park & Jeong (2022)	DL-based industrial system	Mask manufacturing inspection	Improved productivity during COVID-19
Rajan et al. (2021)	CNN + embedded system	Bolt defect detection	Efficient real-time defect identification
Moru & Borro (2020)	Machine vision algorithm	Gear inspection	High calibration accuracy (0.06 pixels error)

IV. CONCLUSION

The review of automated quality inspection systems using machine vision techniques highlights their significant role in transforming modern manufacturing industries. Traditional manual inspection methods are increasingly being replaced by intelligent, automated vision-based systems due to their higher accuracy, consistency, and real-time processing capabilities. The integration of machine vision with artificial intelligence, deep learning, and industrial automation technologies has enabled manufacturers to achieve more reliable defect detection, improved process control, and enhanced production efficiency. Recent studies demonstrate that machine vision systems are being successfully applied across various industrial domains, including automotive assembly, electronics manufacturing, gear inspection, and CNC machining. Techniques such as convolutional neural networks, support vector regression, and hybrid vision-PLC systems have shown strong performance in detecting defects and ensuring product quality. These advancements also support the shift toward Industry 4.0, where smart factories rely heavily on data-driven decision-making and automated monitoring systems. However, despite these technological improvements, challenges such as high implementation costs, sensitivity to environmental conditions, limited training datasets, and integration difficulties still restrict widespread adoption, particularly in small and medium-sized enterprises. Addressing these limitations is essential for broader industrial deployment. Overall, machine vision-based quality inspection systems represent a highly effective solution for achieving precision manufacturing and operational excellence. Their continued development is expected to further enhance industrial automation and reduce human dependency in inspection processes.

V. FUTURE SCOPE

- **Edge AI Integration in Inspection Systems:** Future machine vision systems will increasingly use edge computing and lightweight AI models, enabling real-time defect detection directly on industrial devices without relying heavily on cloud processing. This will reduce latency and improve responsiveness in high-speed manufacturing lines.
- **Self-Supervised and Unsupervised Learning Models:** To overcome the limitation of labeled datasets, future systems will adopt self-supervised and unsupervised learning techniques, allowing machines to learn defect patterns with minimal human intervention and data annotation.
- **3D Vision and Multisensor Fusion:** Advanced 3D imaging, LiDAR, and multisensor fusion (thermal, infrared, and hyperspectral imaging) will improve defect detection accuracy, especially for complex geometries and hidden surface flaws in industrial components.
- **Integration with Digital Twin Technology:** Machine vision systems will be combined with digital twins to simulate production processes, predict defects, and optimize inspection strategies before physical manufacturing occurs.
- **Augmented Reality (AR)-Assisted Inspection:** AR-based visualization will enhance human–machine interaction by overlaying defect information in real time, improving decision-making and reducing inspection errors.
- **Low-Cost Scalable Solutions for SMEs:** Future research will focus on developing affordable, modular, and plug-and-play machine vision systems to promote adoption in small and medium-sized enterprises.
- **AI-Driven Predictive Quality Control:** Instead of only detecting defects, future systems will predict potential failures during production, enabling preventive actions and reducing waste.
- **Cyber-Physical System Integration (Industry 5.0):** Machine vision will evolve into fully integrated cyber-physical systems supporting human-centric, sustainable, and highly adaptive smart manufacturing environments.

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