An Overview of Recent Advancements in Machine Vision for Industrial Defect Detection

# Abstract

This paper presents a comprehensive review of advancements in Machine Vision Systems (MVS) for smart manufacturing and industrial quality control inspections, drawing from a range of studies that highlight advancements in optical systems, image acquisition

techniques, and the pivotal role of deep learning methodologies. It addresses key components of visual inspection systems, including optical illumination, image acquisition, and image processing, examining their impact on detection accuracy, efficiency, and robustness. The

review identifies prevalent methods and future trends, offering insights for researchers and practitioners in manufacturing, computer vision, and quality control. Ultimately, this review aims to present the recent trends in the field of machine vision and image processing for

defect detection in industrial applications, along with highlighting the research gaps for future work.

**Keywords:** Machine vision, defect detection, image processing, deep learning, industrial automation, quality control.

# Introduction

Manufacturing, technology, and society experienced a number of changes throughout the Industrial Revolution. Fig. 1 illustrates the four phases of the industrial revolution. Industry

1.0 refers to the introduction of steam-powered engines and the subsequent mechanization of production operations [10,11]. Industry 2.0 concentrated on using energy to support mass production in response to rising demand. Industry 3.0 made additional advancements in the use of robots, automation, and computers. Industry 4.0 refers to contemporary manufacturing, also known

as Cyber-Physical Systems (CPS), which makes use of artificial intelligence (AI), the Industrial Internet of things, and machine learning. [1]

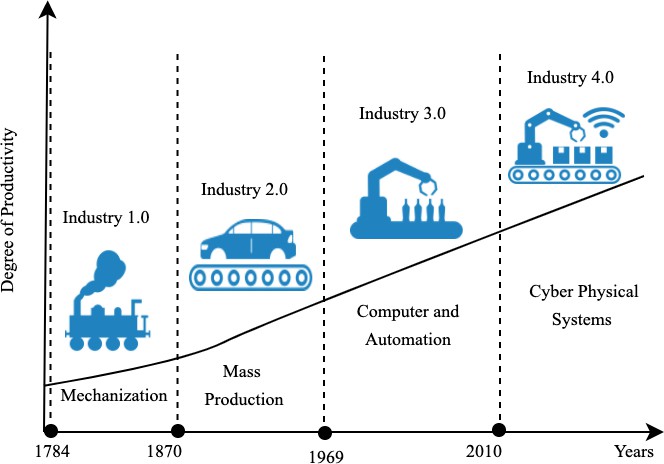


Figure:1 Manufacturing Evolution[1]

In modern manufacturing, quality control is paramount for maintaining competitiveness and meeting stringent industry standards. Manufacturing processes inherently transform raw

materials into finished products through a series of intricate operations that significantly impact the production line's overall efficiency and output quality. Defects and inconsistencies can lead to substantial economic losses, reputational damage, and potential safety hazards. [2,12,13]

The integration of machine vision systems has significantly enhanced defect detection in industrial manufacturing by improving efficiency, quality, and reliability. Traditional manual inspection methods are often labour-intensive, subjective, and prone to errors, whereas

machine vision offers a non-contact and non-destructive approach that facilitates information integration, automation, and precise control [14-16]. Defect detection is an effective method to reduce the adverse impact of product defects and as industries increasingly adopt Industry 4.0 principles, the integration of smart technologies like Machine Vision Systems (MVS) has

become essential for enhancing quality control processes.[3]

MVS offers a robust solution for real-time monitoring, defect detection, and automated inspection, ensuring consistent product quality and operational efficiency. By combining sensors, cameras, and sophisticated computer-based neural network techniques, MVS can analyse data, provide immediate feedback, and proactively mitigate potential issues[2,17-20]. This proactive approach is crucial for minimising resource wastage, reducing environmental impact, and optimising production workflows.

# Historical Context and Evolution of Machine Vision Systems

The concept of machine vision has evolved significantly over the decades, transitioning from basic image processing techniques to sophisticated AI-driven systems. Early MVS relied on manual feature extraction and traditional algorithms, which were often limited by their inability to handle complex patterns and variations. However, with the advent of AI and deep learning, MVS have achieved unprecedented levels of accuracy, speed, and versatility.[1]

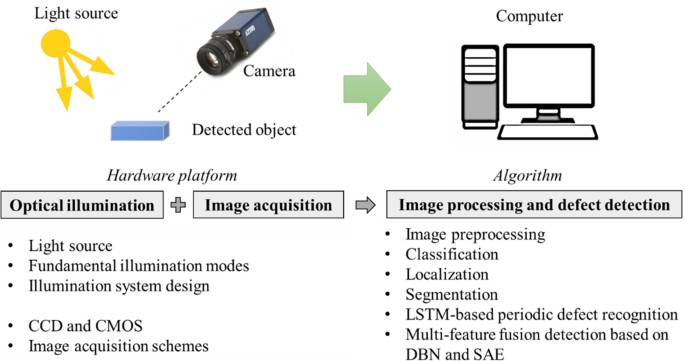
The development of machine vision systems involves several key stages as shown in figure 2[1]:

**Optical Illumination:** Obtaining high-quality images is crucial for the success of any visual inspection system. Effective optical illumination overcomes environmental lighting interference, ensures image stability, and provides high contrast, making important object

features visible while reducing undesired ones[1].

**Image Acquisition:** This stage involves using CCD cameras or other imaging hardware to capture images of the object under inspection[1].

**Image Processing and Analysis:** Acquired images undergo processing to extract relevant features and detect defects. This may involve traditional image processing techniques or advanced deep learning algorithms for classification, localisation, and segmentation[1].

Figure 2 : Key stages of MVS[1]

1. **Optical Illumination Techniques** Optical illumination plays a vital role in visual inspection, ensuring image stability and high contrast by mitigating environmental lighting interference. The primary objective is to enhance the visibility of critical object features while minimising unwanted elements[1].

# Traditional Illumination Methods

**Forward Lighting:** The most common illumination method, forward lighting, positions the light source and camera on the same side of the object, making it suitable for detecting

surface defects and capturing intricate details11. Variations include bright field, dark field, and low angle dark field forward lighting, each tailored to specific applications[1].

**Coaxial Forward Lighting:** This method employs a half mirror to create light coaxial with the lens, providing uniform illumination and reducing reflections, thereby improving the accuracy of defect detection[1].

**Back Lighting:** Placing the light source behind the object, back lighting highlights the

shadow of opaque objects and reveals the interior of transparent objects, making it ideal for shape and dimension detection[1].

* 1. **Auxiliary Optical Devices** Auxiliary optical devices such as filters, reflectors and polarizers are used to refine the illumination. These components help eliminate noise, enhance the signal-to-noise ratio (SNR), and optimise lighting conditions for specific inspection requirements[1].
  2. **Illumination System Design** Effective illumination system design involves analysing project-specific factors such as object characteristics, motion state, and surrounding

environment13. This analysis informs the selection of appropriate light sources, colours, and illumination methods.[1]

1. **Image Acquisition** Image acquisition is a critical component of machine vision systems, involving the use of image sensors to convert light into digital signals. The design of image acquisition systems must consider factors such as camera type, resolution, and the specific requirements of the inspection task.[1]

# Camera Systems

**Area Scan Cameras:** These cameras capture two-dimensional images in a single frame and are suitable for applications where the object is stationary or moving slowly.

**Line Scan Cameras:** Line scan cameras capture images one line at a time, making them ideal for inspecting continuously moving objects such as web materials.

**3D Machine Vision:** This technology utilises techniques such as time-of-flight, stereo vision, and structured light to capture three-dimensional data, providing in-depth analytical

capabilities for dimension measurement, defect detection and robot guidance.

**Plenoptic Cameras:** Plenoptic cameras offer a compact design for integrated manufacturing, capturing both 2D and 3D information in a single measurement step, making them suitable for quality detection in micro-domains.[1]

**Multispectral Imaging:** Multispectral imaging systems combine multiple photosensitive imaging devices to capture wavelength-specific characteristics, enhancing the representation of object features in the collected images.[1]

* 1. **Multiple Views** For parts with complex structures, acquiring images from multiple views can provide comprehensive information for inspection. Multi-view systems employ different image pre-processing and feature extraction methods to enhance and detect surface defects.[1]

1. **Image Processing and Defect Detection** Image processing and defect detection are essential for extracting meaningful information from acquired images and identifying defects. These tasks involve a range of techniques, from traditional image processing methods to advanced deep learning algorithms.[1]
   1. **Traditional Image Processing Methods** Traditional image processing methods include techniques such as thresholding, edge detection, morphological operations, and feature

extraction. These methods are used to enhance image quality, segment regions of interest, and extract relevant features for defect classification.[3]

* 1. **Deep Learning-Based Methods** Deep learning has revolutionised image processing and defect detection, offering powerful tools for automated feature extraction and classification. Convolutional Neural Networks (CNNs) are particularly well-suited for image analysis, enabling the automatic learning of complex features from raw data.[1]

**Defect Classification:** CNNs have been widely applied for defect classification in various industries, demonstrating superior performance compared to traditional methods. Pre-trained CNN models can achieve high accuracy with small datasets, making them effective for

surface quality inspection.[1]

**Defect Localisation:** Techniques such as Faster R-CNN and Single Shot Multibox Detector (SSD) are used for object detection and localisation, enabling the rapid and precise positioning of defects.[1]

**Defect Segmentation:** Fully Convolutional Networks (FCNs) and other segmentation-based methods are employed to identify and measure defects at the pixel level, providing detailed information about defect shape and size.[1]

# Applications of Machine Vision Systems in Industry

MVS are employed across various industries for quality control, process automation, and defect detection[4]. Some notable applications include:

**Automotive Industry:** MVS are used for inspecting car body panels, engine components, and other critical parts. They can detect surface defects, dimensional inaccuracies, and assembly errors, ensuring high-quality standards.[4]

**Electronics Manufacturing:** MVS are essential for inspecting Printed Circuit Boards (PCBs), semiconductor wafers, and electronic components. They can identify missing components, solder joint defects, and other anomalies, improving product reliability.[5]

**Food and Beverage Industry:** MVS are used for inspecting food products for defects, contaminants, and packaging errors. They can also assess the ripeness and quality of fruits and vegetables, ensuring consistent product quality.[6]

**Pharmaceutical Industry:** MVS are employed for inspecting tablets, capsules, and packaging materials. They can detect missing tablets, incorrect labelling, and other errors, ensuring patient safety and regulatory compliance.[7]

**Textile Industry:** MVS are used for fabric defect detection, identifying flaws such as tears, stains, and weaving irregularities. This helps improve fabric quality and reduce waste.[8]

# Challenges and Limitations

Despite the numerous benefits of MVS, several challenges and limitations need to be addressed.

**Technical Constraints:** Implementing MVS can be technically challenging, requiring

expertise in optics, image processing, and AI. Integrating MVS with existing manufacturing systems may also pose difficulties.[4]

**Data Requirements:** Deep learning-based MVS require large amounts of high-quality training data16. Acquiring and labelling sufficient data can be time-consuming and expensive.[1]

**Adaptability and Generalisation:** MVS often struggle to adapt to new products, materials, or manufacturing processes. Developing more adaptable and generalisable AI frameworks is crucial for reducing customisation efforts and improving scalability.[4]

**Computational Resources:** Complex deep learning models require significant computational resources, including high-performance GPUs and specialised hardware. This can increase the cost and complexity of MVS deployment.[4]

# Future Trends and Research Directions

The field of MVS is continually evolving, driven by advancements in AI, sensor technology, and computing infrastructure[4]. Some promising future trends and research directions include:

**Edge Computing:** Deploying MVS at the edge of the network, closer to the manufacturing process, can reduce latency and improve real-time decision-making.[5]

**AI-Driven Defect Segmentation:** Developing more sophisticated AI algorithms for defect segmentation can enable finer-grained analysis and more accurate defect classification.[1]

**Multi-Sensor Fusion:** Combining data from multiple sensors, such as cameras, LiDAR, and thermal sensors, can provide a more comprehensive view of the object under inspection, improving defect detection and process monitoring.[5]

**Explainable AI (XAI):** Incorporating XAI techniques into MVS can provide insights into the decision-making process of AI models, increasing trust and transparency[1].

**Quantum Computing:** Exploring the use of quantum computing for accelerating complex image processing and AI algorithms may offer significant performance gains in the future.[1]

**Integration with Digital Twins:** Integrating MVS with digital twins can enable virtual testing and optimisation of manufacturing processes, reducing the need for physical experimentation.[7]

# Conclusion

Machine Vision Systems (MVS) have emerged as a critical component of modern industrial quality control, offering unparalleled capabilities for real-time monitoring, defect detection, and process automation. The integration of Artificial Intelligence (AI) and deep learning has further enhanced the performance and versatility of MVS, enabling them to tackle complex inspection tasks with remarkable accuracy and efficiency[1]. While challenges such as technical constraints, data requirements, and adaptability remain, ongoing research and development efforts are paving the way for more robust, scalable, and intelligent MVS solutions. By addressing these challenges and capitalising on emerging trends such as edge computing, multi-sensor fusion, and explainable AI, industries can unlock the full potential of MVS, driving significant improvements in product quality, operational efficiency, and overall competitiveness[4].

COMPETING INTERESTS DISCLAIMER:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

# References

1. Ren, Z., Fang, F., Yan, N., & Wu, Y. State of the Art in Defect Detection Based on Machine Vision. International Journal of Precision Engineering and Manufacturing-Green Technology (2022) 9:661–691[1]
2. Sharma, Aman; Kulkarni, Ambarish. Vision System for Smart Manufacturing: A Review[2]
3. Chauhan, Vedang D. PhD Thesis: Vision Based Fault Detection and Classification for Automated Assembly Machine[3]
4. Luhm Silva, Ricardo; Rudek, Marcelo; Szejka, Anderson Luis; Canciglieri Junior, Osiris. Machine Vision Systems for Industrial Quality Control Inspections. 15th IFIP International Conference on Product Lifecycle Management (PLM), Jul 2018, Turin, Italy. Pp.631-641[4]
5. Silva, C.A.d.S.; Paladini, E.P. Smart Machine Vision System to Improve Decision-Making on the Assembly Line. Machines 2025, 13, 98.[5]
6. Medina, Anthony; Bradley, Ryan; Xu, Weiming; Ponce, Pablo; Anthony, Brandon; Molina, Arturo. Learning Manufacturing Computer Vision Systems Using a V-Model Methodology and Project-Based Learning[6]
7. Wu P, He T, Zhu H, et al. Next‐generation machine vision systems incorporating

two‐dimensional materials: progress and perspectives. InfoMat. 2022; 4(1): e12275.[7]

1. Kusuma, Sandy Sidik Wisnu; Saputra, Holam Cahya; Widiastuti, Indah. Manufacturing of Natural Fiber-Reinforced Recycled Polymer–a Systematic Literature Review[8]
2. Ren Z, Fang F, Yan N, Wu Y. State of the art in defect detection based on machine vision. International Journal of Precision Engineering and Manufacturing-Green Technology. 2022 Mar;9(2):661-91.
3. Baygin M, Karakose M, Sarimaden A, Erhan AK. Machine vision based defect detection approach using image processing. In2017 international artificial intelligence and data processing symposium (IDAP) 2017 Sep 16 (pp. 1-5). Ieee.
4. Kumar A. Computer-vision-based fabric defect detection: A survey. IEEE transactions on industrial electronics. 2008 Jan 4;55(1):348-63.
5. Shahrabadi S, Castilla Y, Guevara M, Magalhães LG, Gonzalez D, Adão T. Defect detection in the textile industry using image-based machine learning methods: a brief review. InJournal of Physics: Conference Series 2022 Apr 1 (Vol. 2224, No. 1, p. 012010). IOP Publishing.
6. Li M, Jia J, Lu X, Zhang Y. A method of surface defect detection of irregular industrial products based on machine vision. Wireless Communications and Mobile Computing. 2021;2021(1):6630802.
7. Li M, Jia J, Lu X, Zhang Y. A method of surface defect detection of irregular industrial products based on machine vision. Wireless Communications and Mobile Computing. 2021;2021(1):6630802.
8. Çelik Hİ, Dülger LC, Topalbekiroğlu M. Development of a machine vision system: real-time fabric defect detection and classification with neural networks. The Journal of The Textile Institute. 2014 Jun 3;105(6):575-85.
9. Çelik Hİ, Dülger LC, Topalbekiroğlu M. Development of a machine vision system: real-time fabric defect detection and classification with neural networks. The Journal of The Textile Institute. 2014 Jun 3;105(6):575-85.
10. Qi S, Yang J, Zhong Z. A review on industrial surface defect detection based on deep learning technology. InProceedings of the 2020 3rd international conference on machine learning and machine intelligence 2020 Sep 18 (pp. 24-30).
11. Wang J, Fu P, Gao RX. Machine vision intelligence for product defect inspection based on deep learning and Hough transform. Journal of Manufacturing Systems. 2019 Apr 1;51:52-60.
12. Dong G, Sun S, Wang Z, Wu N, Huang P, Feng H, Pan M. Application of machine vision-based NDT technology in ceramic surface defect detection–a review. Materials Testing. 2022 Feb 23;64(2):202-19.
13. Dlamini S, Kao CY, Su SL, Jeffrey Kuo CF. Development of a real-time machine vision system for functional textile fabric defect detection using a deep YOLOv4 model. Textile Research Journal. 2022 Mar;92(5-6):675-90.