Recent Advancements in Machine Vision Systems for Industrial Defect Detection: A Review

# Abstract

Manufacturing, technology, and society experienced a number of changes throughout the Industrial Revolution. 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. With the advent of AI and deep learning, MVS have achieved unprecedented levels of accuracy, speed, and versatility. 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. 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. The integration of machine vision systems has significantly enhanced defect detection in industrial manufacturing by improving efficiency, quality, and reliability. MVS have wide applications across industries, namely, automotive industry, electronics manufacturing, food and beverage industry, pharmaceutical industry and textile industry. Despite the numerous benefits of MVS, several challenges exist related to technical constraints, data requirements, adaptability and generalisation, and computational resources. The review concluded that 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.

**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]

Deep learning models based on convolutional neural networks (CNN) have had a

lot of success in various computer vision fields, such as recognizing faces, identifying

pedestrians, detecting text in images, and tracking targets. Additionally, these models

are used in a wide range of industrial settings for defect detection. This includes both commercial and industrial applications, such as in the automotive industry for detecting

defects in cars. The deep-learning-based surface defect detection software is employed in

these settings to improve the efficiency and accuracy of the defect detection process [21].

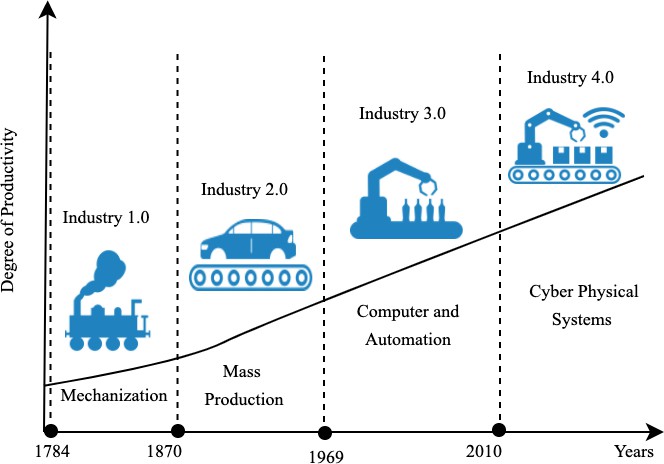


Figure:1 Manufacturing Evolution[1]

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]

Steel is widely used in manufacturing equipment, and steel surface defect inspection is of great significance to the normal operation of steel equipment in manufacturing workshops. The application and promotion of industrial detection robots bring convenience to the defect detection of steel in workshop environments. The automatic inspection robot can scan the steel surface as it moves over the steel. The scanned images are fed into processors for on-line steel surface inspection. The inspected defects are reported for further equipment control and maintenance [22]. Moreover, the widespread use of sensors in industry allows for data acquisition, which, combined with advanced methods of analysis, can significantly improve and optimise production. Therefore, the data can be used not only to monitor the current state of the process and devices, but also to predict this state. The application of predictive methods to sensory data representing the production process, including machine condition, allows for early identification and prediction of the faulty or hazardous process state or machine break down [23].

Anomaly detection plays a critical role in ensuring safe, smooth, and efficient operation of machinery and equipment in industrial environments. With the wide deployment of multimodal sensors and the rapid development of Internet of Things (IoT), the data generated in modern industrial production has become increasingly diverse and complex. The attention-based autoencoder (AAE) and a generative adversarial network (GAN) can capture and fuse rich information from different data sources. Specifically, the AAE captures time-series dependencies and relevant features in each modality, and the GAN introduces adversarial regularization to enhance the model’s ability to reconstruct normal time-series data [25].

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]

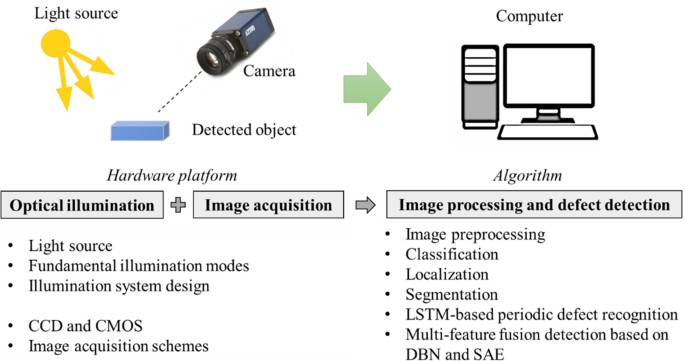
The development of machine vision systems involves several key stages as shown in figure 2[1]:

**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 details. 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

environment. 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] AI-powered automation has emerged as a transformative force in modern industries, driving unprecedented levels of operational efficiency and process optimization. AI enhances the agility of industrial processes by enabling dynamic scheduling and adaptive production systems, capable of responding to changing market demands and supply chain disruptions with minimal human intervention [24].

**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] In a study, a transformer-based model was trained using data obtained from just three locations, and achieved high accuracy in detecting power quality disturbances in electrical power systems. The study demonstrated that the transformer-based model outperformed convolutional [neural networks](https://www.sciencedirect.com/topics/chemical-engineering/neural-network), which are conventional deep learning models for power quality disturbances detection [26].

**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.

**Disclaimer (Artificial intelligence)**

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

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