

Review

Machine Vision Enables Intelligent Manufacturing to Reduce Cost and Increase Efficiency Path and Investment Opportunities

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Abstract: The rapid development of machine vision (MV) has become a key driver of intelligent manufacturing, offering significant opportunities to reduce costs, enhance efficiency, and improve product quality. This review explores the core technologies, methods, and applications of MV, including 2D and 3D imaging, AI-based algorithms, and vision-guided robotics. It highlights practical use cases across industries such as automotive, electronics, food, and pharmaceuticals, demonstrating how MV enables automated inspection, precise assembly, and continuous production monitoring. Furthermore, the paper examines the economic and investment potential of MV, emphasizing its role in labor cost reduction, scrap minimization, and operational optimization. Finally, future trends are discussed, including integration with smart factories, the rise of adaptive AI systems, and emerging business models such as Vision-as-a-Service. By providing a comprehensive overview, this review aims to inform researchers, industry practitioners, and investors about the strategic value and evolving opportunities of machine vision in modern manufacturing.

Keywords: machine vision; intelligent manufacturing; automation; AI algorithms; robotics; smart factory

1. Introduction

In the past decade, the global manufacturing landscape has undergone a profound transformation driven by the integration of advanced technologies and the growing demand for efficiency, quality, and flexibility. Traditional manufacturing systems, largely dependent on human labor and mechanical operations, often struggle to meet the increasing market requirements for higher productivity, shorter lead times, and stricter quality standards. This challenge has catalyzed the rise of intelligent manufacturing, an approach that leverages digital technologies, automation, and data-driven decision-making to optimize production processes. Intelligent manufacturing not only enables faster response to market demands but also promotes sustainable and cost-effective operations across industries. Countries such as Germany, Japan, and the United States have been at the forefront of adopting Industry 4.0 principles, demonstrating the competitive advantages that digitalized production can offer in a globalized economy [1].

A core enabler of intelligent manufacturing is machine vision (MV), a technology that equips machines with the ability to “see,” analyze, and make decisions based on visual information. Machine vision systems typically consist of high-resolution cameras, lighting systems, lenses, and sophisticated image processing software [2]. By capturing and analyzing images in real time, these systems can detect defects, guide robotic operations, monitor production lines, and ensure consistent product quality. Unlike traditional human-based inspection methods, MV offers superior accuracy, speed, and

Published: 15 January 2026



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repeatability, reducing the reliance on labor-intensive processes and minimizing human errors. Over the years, the applications of machine vision have expanded from simple quality control to complex tasks such as predictive maintenance, robotic guidance, and process optimization, making it an indispensable component of modern manufacturing.

This paper aims to provide a comprehensive review of the role of machine vision in enabling intelligent manufacturing, focusing on three main aspects: cost reduction, efficiency improvement, and investment opportunities [3]. The review will first examine the key machine vision technologies and methods, followed by their practical applications across various manufacturing sectors. Subsequently, the discussion will explore the economic implications of MV adoption and identify promising areas for future investment. By integrating technical, economic, and strategic perspectives, this paper seeks to offer insights for researchers, industry practitioners, and investors interested in leveraging machine vision for competitive advantage [4].

To clearly illustrate the differences between traditional manufacturing approaches and intelligent manufacturing enabled by machine vision, Table 1 presents a comparison of key process stages. This table highlights how automation and vision-based technologies have transformed inspection, assembly, and quality control processes, providing a more efficient and reliable production environment.

Table 1. Comparison of Traditional vs. Intelligent Manufacturing Processes.

Process Stage	Traditional Manufacturing	Intelligent Manufacturing
Inspection	Manual	Automated with MV
Assembly	Manual / Semi-automatic	Fully automated
Quality Check	Spot checks	Continuous vision-based monitoring

As shown in Table 1, intelligent manufacturing significantly enhances process efficiency by automating tasks that were previously manual or semi-automatic. Manual inspections, which are prone to variability and human error, are replaced by continuous, machine vision-driven monitoring. Similarly, assembly processes that once required intensive human involvement now benefit from fully automated operations guided by precise visual feedback. Overall, this shift not only improves product quality but also reduces labor costs and increases production throughput, laying the foundation for the subsequent discussions on technology, applications, and investment opportunities in this review.

2. Machine Vision Technologies and Methods

2.1. Core Components of Machine Vision Systems

Machine vision (MV) systems integrate multiple hardware and software components to enable automated visual inspection, measurement, and control in manufacturing environments. The camera serves as the primary data acquisition device, capturing images of the target object with high resolution and precision. Depending on the application, cameras may range from conventional industrial cameras to specialized high-speed or infrared cameras, each optimized for specific lighting conditions and frame rates.

Equally critical is the illumination system, which ensures that the object is properly lit to reveal surface features and defects. Lighting configurations can include diffuse, structured, or directional lighting, and may utilize visible, infrared, or ultraviolet spectra depending on the inspection requirements. Proper illumination minimizes shadows and reflections, allowing the vision algorithms to extract accurate information [5].

Lenses play a vital role in focusing the image onto the sensor while maintaining spatial accuracy and minimizing distortion. The choice of lens—fixed, zoom, telecentric, or wide-angle—depends on factors such as field of view, working distance, and resolution.

Finally, the image processing software interprets the captured images using algorithms for feature extraction, defect detection, measurement, and pattern recognition.

Advanced software solutions often incorporate artificial intelligence (AI) and machine learning techniques to improve adaptability, accuracy, and decision-making speed. Together, these components form a cohesive system capable of performing tasks previously reliant on human vision and judgment [6].

2.2. Classification of Machine Vision Technologies

Machine vision technologies can be broadly categorized based on the type of image data and deployment method. 2D imaging systems capture planar images of the target and are widely used for applications such as surface inspection, barcode reading, and dimensional measurement. Their main advantages include low cost, simplicity, and fast processing speeds, making them suitable for high-volume production lines. However, 2D imaging is limited in its ability to capture depth information, which is essential for precise 3D measurement or complex object recognition.

3D imaging systems, by contrast, reconstruct the three-dimensional shape of objects using techniques such as stereo vision, structured light, time-of-flight, or laser scanning. These systems provide accurate shape measurements, surface profiles, and spatial positioning information, enabling precise robotic guidance, assembly, and defect detection for complex geometries. The trade-offs include higher cost, increased computational complexity, and more sophisticated calibration requirements [7].

In addition to dimensional categorization, MV systems can also be deployed as online (real-time) or offline (batch) inspection solutions. Online systems are integrated into production lines for continuous monitoring, offering immediate feedback and process control. Offline systems, on the other hand, analyze objects in controlled environments after production, suitable for high-precision measurements or research purposes where speed is less critical.

2.3. Key Methods in Machine Vision

The effectiveness of MV systems depends heavily on the algorithms and methods used for image analysis. Image acquisition is the first step, where raw visual data is captured and pre-processed to enhance contrast, reduce noise, and normalize illumination conditions. Once acquired, image processing algorithms extract relevant features such as edges, textures, shapes, and color patterns. Common techniques include thresholding, filtering, morphological operations, and contour analysis.

Pattern recognition and defect detection are essential for quality assurance. Pattern recognition algorithms classify objects based on their visual characteristics, enabling automated sorting or identification. Defect detection algorithms identify anomalies such as scratches, cracks, misalignments, or missing components. With the advent of AI-based vision, machine learning models can now learn from large datasets to recognize complex patterns, detect subtle defects, and adapt to variations in the manufacturing process.

To summarize and compare these key methods, Table 2 presents a concise overview of the main machine vision approaches, their strengths, and their limitations.

Table 2. Comparison of Machine Vision Methods.

Method	Strengths	Limitations
2D Imaging	Low cost, fast processing	Limited depth information
3D Imaging	Accurate shape measurement	Higher cost, complex setup
AI-based Vision	Adaptive, learns patterns	Requires large datasets

As shown in Table 2, each machine vision method offers distinct advantages and trade-offs. 2D imaging remains attractive for high-speed, planar inspections due to its simplicity and affordability. 3D imaging provides greater precision and spatial understanding but demands more sophisticated setup and higher investment. AI-based vision, while computationally intensive and data-dependent, introduces adaptive

capabilities that can significantly enhance defect detection, process monitoring, and automation. Understanding the characteristics of each method allows manufacturers to select the most appropriate MV solution for their specific production requirements and efficiency goals.

3. Applications of Machine Vision in Manufacturing

3.1. Quality Control and Defect Detection

One of the most established applications of machine vision in manufacturing is quality control and defect detection. In traditional production lines, quality inspection often relies on human operators who manually examine products for defects such as scratches, cracks, misalignments, or surface inconsistencies. This manual approach is inherently prone to human error, fatigue, and subjectivity, leading to variability in inspection results and potential product recalls [8].

Machine vision systems address these limitations by providing automated, high-speed, and consistent inspection capabilities. Cameras and sensors capture detailed images of each product, which are analyzed in real time using image processing algorithms to detect anomalies or deviations from design specifications. Advanced techniques, such as AI-based pattern recognition, allow systems to learn from historical defect data and identify even subtle defects that may be overlooked by human inspectors.

Industries such as automotive manufacturing rely heavily on machine vision for surface inspections of car bodies, ensuring paint uniformity and detecting scratches or dents before assembly. Similarly, electronics manufacturers use vision systems to verify the correct placement and soldering of components on printed circuit boards (PCBs). By reducing scrap, minimizing rework, and maintaining consistent product quality, machine vision contributes directly to operational efficiency and cost savings [9].

3.2. Automation in Assembly and Robotics Guidance

Beyond inspection, machine vision plays a critical role in automated assembly processes and robotic guidance. Robots equipped with vision systems can locate, identify, and manipulate parts with high precision, enabling fully automated assembly operations. Vision-guided robotics eliminates reliance on human dexterity and judgment, which is particularly valuable for tasks involving small, delicate, or complex components.

For example, in automotive assembly lines, robots use 3D vision to position and align parts such as engines, doors, and dashboards with sub-millimeter accuracy. In the electronics sector, vision-guided pick-and-place robots accurately place microchips and components on PCBs, ensuring precise alignment and reducing assembly errors. Similarly, in medical device manufacturing, vision-assisted robots assemble intricate components, ensuring compliance with strict regulatory standards [10].

Machine vision also supports real-time adaptive control, where robots adjust their actions based on visual feedback. This adaptability is crucial when dealing with variations in part shape, size, or position, enhancing production flexibility and throughput. By combining vision and robotics, manufacturers can achieve high precision, faster cycle times, and reduced dependency on manual labor, all of which contribute to operational efficiency and cost reduction.

3.3. Process Optimization and Production Monitoring

Machine vision systems are increasingly used for process optimization and production monitoring, extending beyond individual inspections or assembly tasks to provide a holistic view of manufacturing operations. By continuously capturing and analyzing visual data from production lines, MV systems can detect anomalies, bottlenecks, or deviations in real time, allowing manufacturers to implement corrective measures proactively [11].

For instance, in the food industry, vision systems monitor conveyor belts to detect improperly packaged or mislabeled products, preventing defective items from reaching customers. In pharmaceutical manufacturing, machine vision ensures the correct filling, labeling, and sealing of medicine bottles or blister packs, maintaining compliance with stringent quality regulations. Across industries, continuous monitoring reduces downtime, prevents waste, and supports predictive maintenance by identifying equipment wear or misalignment before failures occur.

To summarize the key application areas, Table 3 presents the typical tasks and benefits of machine vision in manufacturing.

Table 3. Key Application Areas of Machine Vision in Manufacturing.

Application	Typical Tasks	Benefits
Quality Control	Surface defect detection	Reduce scrap, improve yield
Robotics Guidance	Part positioning, assembly	Increase precision
Process Monitoring	Line inspection, anomaly detection	Reduce downtime

As illustrated in Table 3, machine vision serves as a versatile tool across multiple stages of manufacturing. Quality control applications enhance product reliability and reduce defects, robotics guidance improves assembly precision and flexibility, and process monitoring optimizes overall production efficiency. Collectively, these applications demonstrate the transformative potential of machine vision, highlighting its contribution not only to operational improvements but also to economic benefits through reduced labor costs, higher throughput, and minimized waste. By integrating vision technologies into manufacturing workflows, companies can achieve a more intelligent, responsive, and cost-effective production environment.

4. Cost Reduction and Efficiency Improvement

4.1. Labor Cost Reduction and Production Efficiency

One of the most immediate and measurable benefits of implementing machine vision in manufacturing is the reduction of labor costs. Traditional production lines rely heavily on human operators for inspection, assembly, and monitoring tasks. These manual operations are not only time-consuming but also subject to variability due to fatigue, skill differences, and human error. By integrating machine vision systems, many of these tasks can be automated, significantly decreasing the need for manual labor while maintaining or improving quality standards [12].

Machine vision enables continuous, high-speed inspection of products, which directly translates into increased production efficiency. For instance, automated visual inspection can process hundreds of items per minute without breaks, whereas human inspectors require regular rest periods and are limited by visual acuity. Additionally, vision-guided robots can perform assembly and handling tasks faster and more accurately than human operators, resulting in higher throughput and shorter cycle times.

The adoption of machine vision also facilitates process standardization and consistency. Automated systems operate according to predefined parameters, ensuring that every product is inspected or assembled in the same manner. This consistency reduces variability in production quality, which is critical for industries with stringent quality requirements, such as automotive, electronics, and pharmaceuticals. By minimizing labor dependency and enhancing production speed, machine vision not only reduces operational costs but also improves overall competitiveness in global markets.

4.2. Error Reduction and Scrap Minimization

Beyond labor and speed, machine vision plays a crucial role in reducing errors and minimizing defective products. Human inspection and manual assembly are inherently prone to mistakes, which can lead to increased scrap rates, rework, and even customer

returns. Machine vision addresses these challenges by providing precise, real-time analysis and feedback, allowing manufacturers to detect and correct defects before products leave the production line.

Key benefits of machine vision in error reduction and scrap minimization include:

- 1) Defect detection at micro levels: Machine vision can identify minor surface imperfections, misalignments, or assembly errors that may be missed by human inspectors.
- 2) Predictive error prevention: By continuously monitoring the production process, vision systems can identify early signs of deviations, allowing operators to adjust parameters and prevent defects.
- 3) Waste reduction: Automated detection and sorting of defective products prevent defective items from reaching downstream processes, reducing material waste.
- 4) Consistent quality metrics: Real-time data collected by vision systems enables manufacturers to track defect rates, identify recurring issues, and implement corrective actions.

When comparing traditional production lines with machine vision-enabled lines, the economic advantages are evident. In conventional setups, defect detection relies on periodic sampling, leaving a significant portion of the production batch unchecked and increasing the risk of quality issues. By contrast, continuous machine vision inspection ensures that every product is verified, dramatically lowering the cost associated with rework, scrap, and warranty claims.

Moreover, the integration of machine vision often results in faster return on investment (ROI). While the initial capital expenditure for cameras, lighting, and processing software may be significant, the long-term savings from reduced labor costs, higher throughput, and minimized waste outweigh the upfront investment. Companies adopting machine vision can achieve more predictable production schedules, lower operational variability, and higher customer satisfaction, positioning themselves for sustainable growth and competitive advantage.

In summary, machine vision transforms traditional manufacturing economics by simultaneously reducing labor dependency, improving production speed, enhancing quality consistency, and minimizing scrap. These combined effects not only cut operational costs but also provide manufacturers with a more reliable, efficient, and scalable production environment, forming a solid foundation for strategic investment and technological innovation.

5. Investment Opportunities and Market Trends

The machine vision market is positioned at the heart of the global smart-manufacturing revolution, presenting compelling opportunities for investors who seek exposure to automation, artificial intelligence, and Industry 4.0. This section explores the current market scale, emerging investment domains, risk-reward trade-offs, and viable business models in the machine vision space.

5.1. Global Market Size and Growth

The global machine vision market is expanding rapidly in response to rising demand for automated inspection, robotics guidance, and smart factories. The market was valued at approximately USD 11.6 billion in 2024, and it is projected to grow to around USD 22.6 billion by 2032, representing a compound annual growth rate (CAGR) of roughly 8.8%.

Parallelly, the industrial production machine vision systems market — a subset focused on manufacturing — was about USD 13.7 billion in 2024, and is forecast to reach USD 31.2 billion by 2033, growing at a CAGR of 9.4%.

On the technology front, the deep-learning-based machine vision segment is also expanding strongly, expected to grow from USD 3.6 billion in 2021 to USD 9.3 billion by 2029, with a CAGR of 12.5%.

In China specifically, the 2023 market for machine vision reached 185 billion RMB, and it is projected to exceed 395 billion RMB by 2028, with a CAGR of approximately 17.5%.

These numbers together underscore the strong and sustained global momentum in machine vision, particularly driven by smart manufacturing trends.

5.2. Emerging Investment Domains

Based on technological and industrial trends, several high-potential areas stand out for investment:

1) AI Vision Algorithms

The integration of deep learning into vision systems is enabling more sophisticated defect detection, anomaly recognition, and pattern classification. Investors can support startups or platforms building adaptive vision models that learn from large image datasets.

Generative AI and data augmentation techniques are also emerging, improving model robustness and reducing labeling costs.

2) Robotic Vision / Vision-Guided Robotics

As robots increasingly dominate assembly lines, demand for 3D vision (time-of-flight, structured light, stereo) is surging to guide pick-and-place, alignment, and manipulation in unstructured environments.

Companies providing embedded vision for mobile robots, collaborative robots, or autonomous vehicles are particularly attractive given the convergence of robotics and vision technologies.

3) Smart Factory Integration

Vision systems are increasingly integrated into broader factory architectures for predictive maintenance, real-time quality monitoring, and process optimization.

Vision-as-a-Service (VaaS) models — where factories lease vision hardware and pay for analytics or inspection as a service — are lowering the adoption barrier for small and mid-size manufacturers.

5.3. Investment Risks and Return Analysis

While machine vision is highly promising, investors must weigh associated risks:

- 1) High initial capital investment: Deploying vision systems, especially 3D or AI-based, requires substantial upfront costs in hardware, software, integration, and calibration.
- 2) Data and model risk: AI-based vision requires large, high-quality datasets. Poor data or biased images can degrade performance, and retraining models can be costly.
- 3) Integration and technical complexity: Integrating vision systems into legacy manufacturing lines can be challenging. Expertise in optics, lighting, software, and system integration is essential.
- 4) Cybersecurity and operational risk: As vision systems become connected to factory networks, they introduce new vulnerabilities. Ensuring reliable edge AI, network security, and data integrity is critical.
- 5) Regulatory and standard risks: In safety-critical industries such as automotive or medical devices, compliance with standards and regulations may impose additional development burdens.

On the return side, successful investments can yield significant cost savings, productivity gains, and long-term contracts. Vision-as-a-Service or rental models reduce CAPEX risk for clients while providing predictable recurring revenue for providers.

Vision integration also often leads to rapid ROI through reduced scrap, fewer defects, and lower labor costs.

5.4. Business Models & Financing Opportunities

Several business models have emerged or are emerging:

- 1) Hardware + Software Platforms: Companies sell cameras, lighting, lenses, and proprietary vision software.
- 2) Vision-as-a-Service (VaaS): Subscription-based or usage-based models allow manufacturers to pay for inspection or analytics services without owning the full system.
- 3) Edge-AI Vision Platforms: Companies provide embedded vision processors or edge inference devices, monetizing through license fees or per-device deployment.
- 4) Data & Analytics Services: Vision systems generate large volumes of image data; companies offer analytics platforms or predictive maintenance dashboards.
- 5) Collaborative Partnerships & Joint Ventures: Partnerships between AI developers, hardware manufacturers, system integrators, and OEMs are increasingly common.

Venture capital and growth equity are actively flowing into AI vision startups, particularly in deep learning, robotics, and edge compute. Established industrial players also invest through internal R&D or acquisitions to accelerate smart factory adoption.

6. Conclusion and Future Directions

Machine vision has emerged as a cornerstone of intelligent manufacturing, fundamentally transforming traditional production processes across industries. By enabling automated inspection, precise assembly, and continuous process monitoring, machine vision systems have demonstrated their ability to enhance product quality, reduce labor dependency, and improve operational efficiency. Compared to conventional manufacturing lines, vision-enabled systems not only minimize human error but also facilitate higher consistency, faster throughput, and more predictable outcomes. As highlighted throughout this review, these advantages translate directly into cost reductions, lower scrap rates, and more streamlined production workflows, making machine vision a highly valuable investment for manufacturers seeking competitive advantage.

The technological landscape of machine vision is evolving rapidly, driven by advances in artificial intelligence, deep learning, 3D imaging, and edge computing. AI-based vision systems, in particular, are enabling adaptive and self-learning capabilities, allowing inspection and assembly processes to handle more complex products and dynamic environments. Meanwhile, integration with robotics and smart factory infrastructures is extending the scope of machine vision beyond isolated tasks, transforming it into a key component of holistic Industry 4.0 solutions. Future developments are expected to focus on increasing the speed, accuracy, and affordability of vision systems, as well as enhancing their ability to operate in unstructured or variable manufacturing conditions.

From a strategic perspective, the adoption of machine vision presents not only operational benefits but also significant investment potential. Companies that implement vision systems effectively can achieve faster returns on investment through labor cost savings, reduced rework, and improved product quality. Simultaneously, the market for machine vision technologies continues to expand, offering opportunities for startups, hardware suppliers, AI developers, and system integrators to capture value. Emerging business models, such as Vision-as-a-Service (VaaS) and edge-AI platforms, further lower the entry barrier for manufacturers while creating recurring revenue streams for providers.

In conclusion, machine vision represents a transformative force in modern manufacturing. Its ability to enhance efficiency, reduce costs, and improve quality positions it as a strategic enabler of intelligent production. Looking forward, continued technological innovation, broader adoption across industries, and the development of integrated solutions will further strengthen its role in shaping the future of manufacturing. By embracing machine vision, manufacturers and investors alike can capitalize on its dual value: operational excellence and sustainable economic opportunity.

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