From Manual to Intelligent: Large AI Models Reshaping Industrial Inspection Paradigms

Fanghui Li[1], Jia Li[2,3,*]
[1]*Machinery Industry Information Research Institute, Beijing, China*
[2]*China Electronics Standardization Institute, Beijing, China*
[3]*Beijing University of Technology, Beijing, China*
**Corresponding Author*

Abstract: Industrial inspection, a core component of manufacturing quality control, is undergoing a profound transformation driven by artificial intelligence (AI), particularly multimodal large models. The study systematically examines the technological evolution of AI-enabled industrial inspection. It evaluates its contributions to efficiency improvement, accuracy enhancement, cost optimization, and process restructuring from the dual perspectives of "value creation" and "potential risks." Key challenges related to data security, model reliability, deployment costs, and talent shortages are also identified. On this basis, targeted development strategies are proposed across technological, economic, human resource, and standardization dimensions. The study aims to provide both theoretical support and practical guidance for implementing large AI models in industrial inspection and promoting industrial upgrading.

Keywords: Large AI Models; Industrial Inspection; Technological Paradigm Shift; Implementation Framework

1. Introduction

With the acceleration of global industrialization, the manufacturing industry faces unprecedented challenges and opportunities. The rapid development of intelligent and automated technologies has positioned production efficiency and product quality as key factors in determining enterprise competitiveness. Industrial inspection, a critical component of quality control, has long been hindered by inefficiency, limited accuracy, and high subjectivity under traditional approaches[1]. Conventional inspection methods are increasingly inadequate with increasing product diversity, the growing complexity of manufacturing processes, and heightened precision requirements in high-end industries. The emergence of AI—particularly multimodal technologies—provides new pathways for industrial inspection, enabling a paradigm shift toward high efficiency, high precision, and intelligence.

2. Adaptation Challenges of Traditional Industrial Inspection Methods

Traditional industrial inspection relies on manual quality control and basic automated inspection, which face significant limitations (see Table 1). Manual inspection depends on workers' visual judgment or simple tools to identify defects. While intuitive and flexible, it is constrained by human speed and endurance, making it unsuitable for large-scale production. Fatigue during prolonged shifts and variability in subjective judgment increase the risks of misclassification and missed defects. Moreover, manual inspection requires substantial labor investment, and training skilled workers is time-intensive[2].

Basic automated inspection, which employs sensors, optical instruments, and elementary vision systems, offers improved efficiency and consistency over manual methods but remains restricted to predefined defect types. Its performance is inadequate for products with complex geometries or diverse materials. Additionally, when production lines change or processes are upgraded, these systems cannot autonomously adapt. Instead, algorithms must be redesigned, resulting in low development efficiency, long debugging cycles, and significant constraints on production flexibility and scalability.

3. Implementation Path of Large AI Models Empowering Industrial Inspection

Implementing large AI models in industrial inspection follows a six-step approach: “Requirement-Data-Technology-Integration-Verification-Deployment”(see Figure 1). Each phase is tightly interconnected, leveraging the large model's capabilities in few-shot learning and multimodal fusion to overcome challenges in industrial deployment[3,4].

Table 1. Challenges of Traditional Inspection Method

Challenge	Core Issues	Negative Impact
Limitations in Detection Capability	1. Manual inspection relies solely on the human eye, resulting in weak detection capability. 2. Basic automated inspection only supports pre-defined defect types.	1. Defective products enter the market, leading to increased customer complaint rates. 2. Loss of high-end orders, confining enterprises to low value-added production segments.
Low Inspection Efficiency	1. Manual inspection is slow, often limited to sampling, resulting in incomplete quality coverage. 2. Line changeovers for basic automated inspection require algorithm redesign, leading to lengthy debugging cycles.	1. Production line capacity is constrained, and delivery cycles are prolonged. 2. High risk of batch defects, easily triggering customer claims.
Poor Inspection Accuracy	1. Manual inspection accuracy is unstable, influenced by experience and fatigue. 2. Basic automated inspection lacks sufficient accuracy for complex scenarios.	1. Low pass rates for high-end products, leading to increased production costs. 2. Potential safety hazards in sectors like aerospace and automotive.
Poor Objectivity	1. Manual inspection is highly subjective. 2. Basic automated inspection, while somewhat objective, lacks unified judgment standards.	1. Inconsistent quality standards across multinational factories. 2. Difficulties in adapting to upstream and downstream supply chain requirements.
Weak Generalization Capability	1. Manual inspection has high missed detection rates for new defect types. 2. Basic automated inspection has narrow applicability; line changeovers are costly, and it lacks defect cause analysis and decision-making capabilities.	1. Low production line changeover efficiency, causing delays in the global supply chain. 2. Lagging process optimization, leading to recurring batch defects. 3. Rising labor costs compress corporate profits.
Information Silos	1. Inspection, process, and maintenance data exist in isolation, lacking interoperability. 2. Information flow is inefficient, resulting in long problem response times. 3. Lacks closed-loop capability for "identification-improvement".	1. Multinational corporations face significant challenges in quality control due to difficulties consolidating global data. 2. Slow fault localization leads to extended equipment downtime. 3. Severe production waste and increased product scrap rates.

3.1 Requirement Analysis and Scenario Definition

complex defect recognition challenges—and quantify objectives (e.g., achieving 99.5% defect detection accuracy)[5]. Large AI models parse process documentation and expert knowledge, converting tacit insights into structured information to guide subsequent phases[6].

3.2 Data Collection and Preprocessing

Multi-source data—including product images and production parameters—is gathered via industrial cameras and sensors. Large-model few-shot learning and AIGC technologies mitigate the shortage of real defect data[7].

3.3 Technical Solution Selection and Model Training

The corresponding author should have an asterisk. Select a suitable large model (e.g., DeepSeek-VL2) based on the application scenario. Combine transfer learning and fine-tuning techniques to train the model using preprocessed data. The large model's multimodal fusion capability integrates data such as images and process parameters. The general knowledge accumulated during pre-training significantly reduces the required training sample size, enabling the model to rapidly acquire core detection capabilities[8].

3.4 Hardware and System Integration Deployment

Based on production line requirements for detection latency, deploy the model either at the edge (enabling millisecond-level real-time detection) or in the cloud (supporting multi-line collaboration and model iteration). Integrate the AI inspection system with production line MES, ERP, and other systems to enable real-time feedback of inspection results to production control terminals, forming an automated "inspection-production adjustment" closed loop[9].

3.5 Testing, Validation, and Iterative Optimization

Conduct small-batch production line testing to verify whether the model's defect recognition accuracy and detection speed meet expectations in real-world conditions. Address issues like missed detections or misclassifications by adjusting model parameters based on production feedback and supplementing targeted data, iterating continuously until standardized detection results are achieved[10].

3.6 Scalable Promotion and Continuous Improvement

Following successful validation in a single scenario, horizontally expand AI inspection capabilities to similar production lines or different products. Vertically deepen the large model's generalization and autonomous learning abilities by integrating more scenario data to enhance the model. Drive continuous upgrades to the inspection system, extending value across the entire factory and even the industry[11].

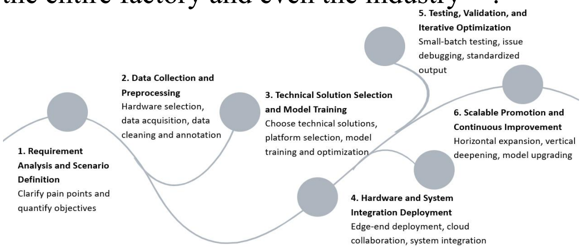

Figure 1. Implementation Path of Large AI Models Empowering Industrial Inspection

4. Core Value of Large AI Models in Industrial Inspection (Positive Impacts)

Large AI models reshape industrial inspections' technical logic and value chain, delivering systematic improvements across four core dimensions: efficiency, accuracy, cost, and process (see Table 2). This approach not only overcomes the technical limitations of traditional inspection methods but also leverages autonomous learning and end-to-end data integration capabilities to elevate industrial inspection from an "isolated process" to an "intelligent hub."

4.1 Efficiency Improvement: Breaking Manual Speed Limits, Ensuring Continuous Production Line Operation

An AI model-driven industrial inspection significantly boosts the production line's inspection processing speed and stability. Leveraging high-speed data mining capabilities, it performs parallel analysis on massive datasets collected by inspection equipment, processing vast amounts of inspection data at speeds far exceeding human capacity. This enables 24/7 uninterrupted operation, eliminating efficiency fluctuations caused by human fatigue. Large AI models' autonomous adaptation capabilities and few-shot learning mechanisms drastically shorten the model deployment cycle for new equipment and processes. This reduces inspection downtime during production line switches, further boosting overall manufacturing efficiency and aligning with the high-speed and flexible demands of modern manufacturing[12,13].

4.2 Accuracy Breakthrough: Enhancing Defect Recognition and Tightening Quality Control

Large AI models integrate multi-source data—including visual, spectral, and sensor inputs—to construct comprehensive defect feature maps, effectively circumventing information blind spots inherent in single-data-modality approaches. Simultaneously, integrating super-resolution technology with advanced visual algorithms enables precise capture of micron-level and even sub-micron-level features. This resolves the missed detection issues of traditional inspection methods for defects such as microcracks and minute deformations, establishing stricter, all-dimensional control over product quality. This capability suits high-precision industries like semiconductors and aerospace[13,14].

4.3 Cost Optimization: Dual Advantages of Reducing Global Enterprise Expenditure

Large AI models optimize industrial inspection cost structures through reduced data requirements and labor expenditures. Regarding data needs, vision models based on Transformer architectures (e.g., MetaSAM2) support few-shot learning, reducing required defect recognition samples by 90%. This significantly shortens model training cycles while minimizing enterprise time and labor costs for data annotation. Regarding labor costs, AI systems can replace manual repetitive inspection tasks, reducing the need for dedicated quality inspectors while eliminating scrap costs caused by human misdetections or missed defects. Furthermore, large models' autonomous learning capabilities reduce manual intervention costs in subsequent model iterations, further compressing long-term operational expenses[13].

4.4 Process Restructuring: Upgrading from "Single Defect Recognition" to "Full-Process Quality Management"

Large AI models possess autonomous learning, optimization, and decision-making capabilities. They rapidly adapt to new inspection requirements in small-sample scenarios, dynamically adjust recognition strategies based on inspection data, generate real-time quality reports, and provide data insights for production. By leveraging large models, enterprises can establish unified fault knowledge bases and knowledge graphs that integrate inspection data, production process parameters, and equipment maintenance records. This enables real-time defect determination and automated generation of diagnostic reports and fault solutions. These provide precise guidance for production process optimization and equipment preventive maintenance, achieving a closed-loop “inspection-analysis-improvement” process[13,15].

Table 2. Positive Impacts of AI Large Models on Industrial Inspection

Impact Dimension	Core Technical Support	Typical Cases
Efficiency Improvement	High-speed data processing, 24/7 uninterrupted operation, self-adaptation to production lines	European forestry giant Södra has adopted an AI strength grading scanner capable of inspecting 240 boards per minute, significantly enhancing production efficiency.
Accuracy Breakthrough	Deep learning feature capture, micron-level recognition, multimodal data fusion	Siemens, in collaboration with Dazhi Technology, has deeply integrated AI models with industrial edge platforms, increasing defect recognition accuracy from 90% to over 99%.
Cost Optimization	Labor replacement reducing salary expenses, few-shot learning lowering data costs, full inspection reducing waste costs, open-source ecosystem lowering barriers	Schaeffler's AI bearing inspection checks 80,000 bearings daily, compatible with over 20 models, saving 80% in labor costs.
Process Restructuring	Fault knowledge base construction, self-learning/optimization/decision-making, autonomous diagnostic report generation	At BMW Group's Regensburg plant, an AI-powered paint inspection line autonomously detects paint defects, classifies them, and triggers automated handling processes, achieving unprecedented levels of paint quality.

5. Potential Risks of Applying AI Models in Industrial Inspection (Negative Impacts)

While large AI models bring technological innovation to industrial inspection, they face four common cross-border challenges: data security, model reliability, cost pressures, and knowledge/talent barriers (see Table 3). These challenges stem from inherent conflicts between technical characteristics and industrial scenarios and are also constrained by external factors such as uneven global industrial development and inconsistent regulations. They impose differentiated pressures on enterprises of varying scales and locations[16].

5.1 Data Security and Privacy Risks: The Conflict between Sensitive Data Flow and Security Requirements

Data security and privacy risks represent the primary barrier to implementing AI in industrial inspection. Industrial inspection data encompasses core process parameters and product design details, forming the bedrock of corporate competitive advantage[17]. However, large model iteration relies on data feedback, and its collection and transmission involve substantial sensitive information regarding production processes and product quality. This risk is particularly heightened in cross-border inspection workflows, where data traverses multiple stages—collection, annotation, and cloud-based training—significantly increasing the probability of leakage. Additionally, different countries have established data security regulations, such as the European Union’s General Data Protection Regulation (GDPR), and the varying requirements of these data regulations make it easy for AI models to violate rules when processing data across borders. This forces multinational corporations to balance the security baseline of "data not leaving the factory" with the efficiency requirement of "model iteration requiring data." While opting for on-premises deployment ensures security through physical isolation, it sacrifices large models' learning and iterative capabilities. Choosing cloud collaboration, on the other hand, exposes companies to data leakage risks.

5.2 Model Reliability Gap: Disconnect Between Laboratory Performance and Industrial Environments

AI model reliability exhibits a significant gap in industrial “zero-tolerance” scenarios. Industrial inspection demands extreme accuracy, yet large models' decision-making processes possess “black-box attributes,” making it impossible to trace the logical chain behind “why a defect was identified.” Once misjudgments occur, enterprises struggle to pinpoint the root cause. Moreover, incomplete data or environmental interference can trigger “AI hallucinations,” generating seemingly plausible yet inaccurate results. However, the diversity of global geographical environments and complex industrial interferences (e.g., high temperatures, dust, voltage fluctuations) can cause sharp performance declines. Open-source models suffer even worse adaptability, failing to meet diverse global industrial scenarios across regions and sectors[3].

5.3 Cost Pressure: High Initial Investment and Long-Term Maintenance Challenges for Widespread Adoption

Cost pressure remains the primary barrier to widespread adoption of AI industrial inspection, significantly impacting SMEs and enterprises in developing nations. Initial deployment requires hardware such as industrial cameras, GPU servers, and robotic arms, alongside costly integration and modification of existing production lines. Long-term maintenance costs include annual fees for high-end GPU servers, replacement expenses for industrial camera lenses (every 2-3 years), and yearly commercial software licensing fees, resulting in substantial cumulative expenditures. This cost burden leads to a “head-heavy” distribution in global AI inspection adoption rates.

5.4 Knowledge and Talent Barriers: Difficulty in Converting Tacit Knowledge and Imbalance in Talent Supply and Demand

Knowledge and talent barriers hinder the advancement of AI industrial inspection toward deeper applications, manifesting in two primary ways. First, tacit knowledge is difficult to structure: AI models' deep decision-making relies on tacit knowledge within industrial domains. However, this knowledge often exists as the experience of senior engineers and cannot be converted into structured data for model input. Consequently, models can only identify defects but cannot assess risks or guide process optimization. Second, There Is a Shortage and an Imbalanced Distribution of Interdisciplinary Talent. Technological advancements have created a demand for "AI + industry" interdisciplinary talent, but traditional workers' knowledge structures are often rigid and challenging to transform. Meanwhile, most high-end talent chooses to work for European and American companies, leading to a severe "brain drain" in developing countries and further exacerbating the imbalance between talent supply and demand. [18].

5.5 International Technology Barrier Risks: Technological Blockades Widen the Global Inspection Capability Gap

International technology barriers are becoming a critical obstacle for developing countries seeking to deploy advanced AI inspection technologies. Technologically leading nations can impose control lists restricting the export of AI-related models, software, and hardware through differentiated policy systems. They can even extend their jurisdictional reach, requiring licenses for models developed overseas if they utilize underlying algorithm frameworks or computing power support from these countries. Furthermore, technologically advanced nations are embedding implicit controls within open-source ecosystems. Even if basic models are made available, their licensing terms may mandate that "training data must be transmitted in real time to servers in the country of origin" or use "data fingerprinting" technologies to track the actual application scenarios of models in developing countries.

Table 3. Negative Impacts of Large AI Models on Industrial Inspection

Challenge Dimension	Core Theoretical Support	Typical Cases
Data Security and Privacy Risks	Cross-border multi-stage flow of sensitive data, conflicts in global data regulations, balance between security and efficiency	1. Samsung experienced a leak of chip secrets due to the use of ChatGPT. 2. According to guidelines issued by the European Data Protection Board (EDPB), the determination of cross-border data transmission requires that both the data exporter (controller or processor) be subject to GDPR jurisdiction.
Model Reliability Gap	Discrepancy between lab and field environments, AI hallucinations, poor adaptability of open-source models	The hallucination rate of GPT-5-thinking-mini is 22%.
Cost Pressure	High initial deployment costs, long-term maintenance expenses, limited affordability for SMEs	NVIDIA's reference design AI server based on the Blackwell architecture, the NVL36 equipped with 36 B200 GPU accelerators, is priced at approximately $2 million.
Knowledge and Talent Barriers	Difficulty in structuring tacit knowledge, imbalance in interdisciplinary talent supply and demand, industrial technology gap	A report titled "The State of AI Talent 2025" released by UK data company Zeki shows that there are 800,000 top AI talents globally (outside of China).
International Technology Barriers	International Technology Barriers	In January 2025, the United States introduced the "AI Diffusion Rule," implementing a three-tier licensing system to restrict the export of chips and model weights. However, due to industry opposition and high complexity, the rule was abolished in May of the same year. Nevertheless, the Bureau of Industry and Security (BIS) indicated that it might reintroduce the policy in the future, emphasizing the necessity of controlling model weights.

6. Development Suggestions and Countermeasures

To more efficiently advance the implementation of large AI models in industrial inspection, it is recommended that key challenges—including security risks, excessive barriers to entry, capability mismatches, and regulatory gaps—be addressed by focusing on four core dimensions: technology, cost, talent, and standards. This approach will ensure the full realization of the value of large AI models within industrial inspection scenarios.

Regarding technological optimization, focus should be placed on enhancing reliability and security[4]. To address data security challenges, a full-chain protection system should be established. A global joint training framework for industrial inspection data based on federated learning and homomorphic encryption should be developed to achieve "data usability without visibility." Enterprises in different countries can retain local data ownership while participating in model iteration through parameter sharing, avoiding compliance risks associated with cross-border data transmission. The "Global Industrial Inspection Data Security Guidelines" should be formulated to unify data classification standards (e.g., "core process data" and "general quality data") and cross-border flow procedures, reducing compliance costs for enterprises. To tackle insufficient model reliability, explainable AI modules should be developed, using visualization tools to display feature weights and logical chains for defect determination, enabling enterprises to trace the root causes of misjudgments. Additionally, dynamic environment adaptive algorithms should be created, leveraging sensor data such as temperature, humidity, and lighting to adjust model parameters in real time, enhancing robustness against complex industrial interference and bridging the gap between laboratory performance and field applications.

Regarding cost management, we recommend establishing a “low-barrier, high-efficiency” implementation pathway[19]. Adopt a “priority-driven” phased deployment strategy, guiding enterprises to apply large AI models to high-risk, high-return inspection tasks (e.g., detecting minute defects in precision components). After demonstrating effectiveness through single-point validation, gradually expand deployment across entire production lines to balance short-term investment with long-term returns. Advance lightweight model technologies to reduce parameter sizes through pruning, quantization, and knowledge distillation. This enables adaptation to mid-to-low-end GPUs or edge computing devices, lowering hardware barriers. Enhance open-source toolchains by providing standardized model fine-tuning templates, industrial data preprocessing plugins, and troubleshooting manuals. This reduces enterprises' technical and time costs for independent development, empowering SMEs to efficiently reuse mature technologies.

Regarding talent cultivation, we recommend building a composite “AI + Industry” competency pipeline[3]. Promote deep integration between the education system and industrial scenarios, and foster global collaboration in educational resources. Courses such as "AI Industrial Inspection Scenario Applications," "Industrial Data Annotation Standards," and "Model Performance Evaluation Methods" should be added to traditional industrial engineering and automation programs to cultivate talent with both industrial process knowledge and AI technical skills. Enterprises should be encouraged to conduct internal tiered training for traditional quality inspectors. An international talent certification mutual recognition mechanism should be established: led by the International Organization for Standardization (ISO), the "Global AI Industrial Inspection Talent Competency Standards" should be developed to standardize competency evaluations and ensure a precise match between talent skills and job requirements. [20].

Regarding standardization, we recommend establishing a unified application specification system[3]. Establish Global Performance Evaluation Standards for AI Industrial Inspection Systems, led by ISO, these standards should define testing methods and thresholds for core metrics such as accuracy, response time, and robustness, preventing enterprises from making erroneous technology selections due to "ambiguous standards." Global annotation and formatting guidelines for industrial inspection data should be developed, unifying standards for defect classification, feature description, and parameter recording to ensure data interoperability and reuse across different enterprises and scenarios, thereby improving model training efficiency. Furthermore, a knowledge base framework for common industrial inspection defects should be established, standardizing definitions of defect characteristics, cause-effect correlations, and solution descriptions to reduce redundant development and adaptation costs in model training and accelerate the technological catch-up process for enterprises in developing countries.

7. Future Outlook

The application of large AI models in industrial inspection will transition from “deep penetration” to “paradigm innovation,” achieving breakthroughs in three key areas: technological upgrades, comprehensive scenario expansion, and value dimension transformation[21]. This evolution will serve as the core engine driving manufacturing's shift from “passive quality inspection” to “proactive quality control” and from “local optimization” to “system-wide upgrades.”

From a technological perspective, multidimensional integration will break traditional inspection limitations[3,21]. Large AI models will achieve deep coordination among multimodal perception, generative intelligence, and cross-technology linkage. They will construct three-dimensional defect maps and detect latent defects through microcurrents and magnetic field variations by integrating visual, acoustic, vibration, spectral, and environmental parameters. Generative AI can automatically generate highly realistic defect samples, shortening adaptation cycles for new scenarios. Large AI models will enable millisecond-level closed-loop cycles for inspection, simulation, and process adjustment when integrated with digital twins, quantum computing, and brain-computer interfaces. This approach not only overcomes traditional computational bottlenecks but also facilitates the conversion of engineers' tacit knowledge. Concurrently, lightweight modeling techniques will adapt large models to mid-to-low-end edge devices, compressing inspection response times to sub-millisecond levels and significantly reducing enterprises' reliance on high-end hardware[12 21].

In terms of application scenarios, large AI models will achieve comprehensive penetration. Detection scopes will extend from internal factory production lines to cross-border remote inspection of raw materials in supply chains and post-sales product maintenance fault diagnosis, ultimately forming a holistic quality control network. Detection processes will expand from finished product defect inspection to include upstream raw material quality prediction, midstream production process monitoring, and downstream inspection equipment health forecasting, comprehensively covering the entire product lifecycle. AI inspection technology will also transcend conventional industrial constraints, extending into extreme scenarios such as chemical reaction product detection under high-temperature and high-pressure conditions, aerospace component inspection amid substantial electromagnetic interference, and unmanned inspection in nuclear radiation environments. Furthermore, AI inspection will accelerate its penetration into traditional manufacturing sectors like ceramics and hardware, enabling SMEs to deploy tailored inspection systems without substantial investment[3,12].

From a value perspective, large AI models will elevate industrial inspection to serve as the intelligent decision-making hub for manufacturing[21]. The predictive decision-making capabilities of large AI models will significantly strengthen, enabling the early anticipation of product quality trends and the reverse guidance of product design processes to mitigate quality risks at their source. Inspection data will become a core asset in manufacturing digitalization. Through analysis and integration by large AI models, this data will be transformed into high-quality decision-making references such as supply chain quality assessment reports and equipment health profiles, thereby driving cross-enterprise and cross-regional quality collaboration. Large AI models will ultimately transform industrial inspection from an isolated quality control step into a data-driven core spanning the entire manufacturing chain, providing critical support for the global manufacturing industry's advancement toward “zero-defect manufacturing” and “intelligent manufacturing.”

8. Conclusion

As a core component of global manufacturing quality control, industrial inspection is fundamentally transforming from traditional methods to an intelligent hub through large AI models. Conventional inspection approaches commonly suffer from low efficiency, poor accuracy, and weak generalization capabilities, making them ill-suited for complex manufacturing demands. Leveraging core features like multimodal fusion and few-shot learning, large AI models deliver systematic empowerment across efficiency gains, accuracy breakthroughs, cost optimization, and process restructuring, effectively overcoming traditional limitations. However, applying large AI models in industrial inspection still faces practical challenges, including data security risks, insufficient model reliability, high cost pressures, and significant knowledge and talent barriers. It is recommended that the practical difficulties in implementing large AI models be addressed through targeted strategies such as technological optimization, cost control, talent cultivation, and standard development. This will promote the continuous deepening of technological integration, the ongoing expansion of application scenarios, and the accelerated realization of an inclusive ecosystem.

References

[1] Yan W , Fan W .Research on the Current Situation and Development of Intelligent Precision Fertilizer Technology[C]//IFIP WG International Conference on Computer and Computing Technologies in Agricultur.2019.
[2] Sun, H., Teo, W., Wong, K., Dong, B., Polzer, J., & Xu, X. (2024). Automating Quality Control on a Shoestring, a Case Study. Machines.
[3] Nguyen, T., Nguyen, P., & Cao, H. (2024). XEdgeAI: A Human-centered Industrial Inspection Framework with Data-centric Explainable Edge AI Approach. Inf. Fusion, 116, 102782.
[4] Schraml, D., & Notni, G. (2024). Synthetic Training Data in AI-Driven Quality Inspection: The Significance of Camera, Lighting, and Noise Parameters. Sensors (Basel, Switzerland), 24.
[5] Schmitt, J., Bönig, J., Borggräfe, T., Beitinger, G., & Deuse, J. (2020). Predictive

model-based quality inspection using Machine Learning and Edge Cloud Computing. Adv. Eng. Informatics, 45, 101101.

[6] Sundaram, S., & Zeid, A. (2023). Artificial Intelligence-Based Smart Quality Inspection for Manufacturing. Micromachines, 14.

[7] Li, S., Lin, X., Xu, W., & Li, J. (2024). AI-Generated Content-Based Edge Learning for Fast and Efficient Few-Shot Defect Detection in IIoT. IEEE Transactions on Services Computing, 17, 3140-3153.

[8] Li, S., Sun, W., Liang, Q., Sun, J., & Liu, C. (2025). Multimodal Fabric Defect Classification Using Channel Switching and Multiscale Feature Fusion. IEEE Transactions on Instrumentation and Measurement, 74, 1-12.

[9] Zant, C., Charrier, Q., Benfriha, K., & Men, P. (2021). Enhanced Manufacturing Execution System "MES" Through a Smart Vision System. Lecture Notes in Mechanical Engineering.

[10] Tantithamthavorn, C., McIntosh, S., Hassan, A., & Matsumoto, K. (2018). The Impact of Automated Parameter Optimization on Defect Prediction Models. IEEE Transactions on Software Engineering, 45, 683-711.

[11] Luculescu, M., Cristea, L., & Boer, A. (2025). Artificial Vision System for Autonomous Mobile Platform Used in Intelligent and Flexible Indoor Environment Inspection. Technologies.

[12] Zou, Y., Hou, R., Zhang, Y., Liu, J., Zhang, Z., & Xue, W. (2025). Research on key technologies of power substation inspection based on large model. , 13552, 135520I - 135520I-7.

[13] Byun, M., Low, M., & Lin, D. (2024). A Multi-Modal AI Inspection System for Laser Labels. TENCON 2024 - 2024 IEEE Region 10 Conference (TENCON), 948-951.

[14] Li, L., Ota, K., & Dong, M. (2018). Deep Learning for Smart Industry: Efficient Manufacture Inspection System With Fog Computing. IEEE Transactions on Industrial Informatics, 14, 4665-4673.

[15] Mohan, V. (2025). Integrated AI Models for Simultaneous Quality Improvement and Risk Reduction in Production Processes. Journal of Information Systems Engineering and Management.

[16] Yang, J., Fu, G., Zhu, W., Cao, Y., Cao, Y., & Yang, M. (2020). A Deep Learning-Based Surface Defect Inspection System Using Multiscale and Channel-Compressed Features. IEEE Transactions on Instrumentation and Measurement, 69, 8032-8042.

[17] Tanisha, J., Rajesh, P., Singh, R., Adhip, K., Stuti, K., & Ajitha, D. (2024). Privacy and data protection challenges in industry 4.0: An AI-driven perspective. World Journal of Advanced Engineering Technology and Sciences.

[18] Pei, J., Wang, R., Yan, P., & Tan, Y. (2025). Quality management in supply chain: Strategic implications and the paradox of AI inspection. Decision Sciences.

[19] Kilsby, P., & Kun, L. (2024). Enabling Intelligent Robotic Visual Inspection in the Railway Industry with Generative AI. 2024 Eighth IEEE International Conference on Robotic Computing (IRC), 275-277.

[20] Kwak, J. (2025). Developing Multidisciplinary Talent for the AI Industry: Key Factors and Strategies. Asia-pacific Journal of Convergent Research Interchange.

[21] Khanam, R., Hussain, M., Hill, R., & Allen, P. (2024). A Comprehensive Review of Convolutional Neural Networks for Defect Detection in Industrial Applications. IEEE Access, 12, 94250-94295.

