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SYSTEM FOR PRODUCT QUALITY ASSESSMENT, DIGITAL IDENTIFICATION, AND AUTOMATIC MANAGEMENT OF DEFECTIVE PRODUCTS DURING THE MANUFACTURING PROCESS

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Abstract. The rapid development of Industry 4.0 technologies has significantly transformed conventional approaches to manufacturing quality control. Modern production systems increasingly require intelligent, real-time, and automated mechanisms capable of identifying product defects, determining product quality status, tracking individual products, and automatically directing defective items to appropriate processing or rejection routes. This study proposes an integrated system for product quality assessment, digital identification, and automatic management of defective products during the manufacturing process. The proposed system combines computer vision, artificial intelligence, digital identification technologies, sensors, programmable logic controllers, industrial communication networks, and automated actuators into a unified cyber-physical architecture. The system captures product images using industrial cameras, processes visual information using artificial intelligence algorithms, determines the quality status and type of defect, associates the inspection result with a unique digital product identifier, and generates an automatic control signal for product sorting. The proposed architecture enables real-time quality monitoring, product traceability, reduction of human-related errors, and automatic separation of defective products. A mathematical model for estimating the time required for defective product detection and actuation is also considered. The study demonstrates that the integration of intelligent inspection and automated material handling can provide a foundation for smart quality control and support the transition toward zero-defect manufacturing.

Keywords: artificial intelligence, product quality assessment, digital identification, defect detection, computer vision, automated inspection, Industry 4.0, PLC, IoT, machine learning, smart manufacturing, product traceability.

Introduction. Manufacturing industries are currently undergoing a fundamental transformation driven by digitalization, automation, artificial intelligence (AI), the Internet of Things (IoT), cyber-physical systems, cloud and edge computing, and advanced robotics. This transformation, commonly associated with Industry 4.0, is changing the principles of production management and quality control. Traditional quality inspection approaches that depend heavily on human operators are increasingly being replaced or supplemented by intelligent systems capable of continuously monitoring production processes and making automated decisions. Product quality is one of the most important factors determining the competitiveness, reliability, safety, and economic efficiency of manufacturing enterprises. A defective product that is not detected in time can move to subsequent technological stages, increase rework costs, consume additional resources, and ultimately reach the customer. Therefore, the early detection and automatic management of defective products are essential components of modern manufacturing systems. Conventional quality inspection methods often rely on visual inspection by trained personnel. Although human inspection can be flexible and effective in many situations, it has several limitations. Operator fatigue, subjective decision-making, variations in experience, reduced attention during repetitive tasks, and limited inspection speed can affect the

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consistency of quality assessment. These limitations become particularly significant in high-speed production lines where hundreds or thousands of products may pass through an inspection point every hour. Computer vision provides an important technological foundation for overcoming these limitations. Industrial cameras can continuously acquire product images, while image-processing and artificial intelligence algorithms can identify deviations from expected product characteristics. In particular, convolutional neural networks (CNNs), object detection models, image segmentation algorithms, and anomaly detection techniques have significantly expanded the capabilities of automated visual inspection. However, detecting a defect alone does not completely solve the manufacturing quality-control problem. In an intelligent production environment, it is also necessary to determine which specific product contains the defect, associate the inspection result with its digital identity, track the product through the manufacturing process, and automatically direct it to an appropriate route. Therefore, product quality assessment should be integrated with digital identification and automated material handling. Digital identification technologies such as QR codes, Data Matrix codes, RFID tags, and other identification mechanisms enable individual products or production batches to be associated with digital records. By connecting the product identifier with the quality-inspection result, it becomes possible to create a digital history of each product. Such information can include production time, production line, batch number, inspection result, defect type, confidence score, and subsequent product destination. The combination of intelligent visual inspection and digital identification creates a more comprehensive quality-management mechanism. The system can establish a relationship between the physical product and its digital representation. This approach improves traceability and enables manufacturers to determine not only whether a product is defective but also when and where the product was manufactured and what actions were taken after inspection. Another important aspect is the automatic management of defective products. Once a defect is detected, the system must generate a control decision and transfer it to the appropriate actuator. Depending on the manufacturing process, the actuator may be a pneumatic cylinder, robotic manipulator, servo mechanism, conveyor diverter, or another automated device. A programmable logic controller (PLC) can coordinate the timing between defect detection and physical product sorting. The objective of this study is therefore to develop a conceptual and technical framework for an integrated system capable of performing three interconnected functions: product quality assessment, digital identification, and automatic management of defective products during manufacturing.

Discussion. The results of the study demonstrate that integrating product quality assessment, digital identification, and automated management of defective products into a unified manufacturing system can significantly improve the efficiency, traceability, and reliability of industrial quality control. Unlike conventional inspection approaches, in which quality assessment is often performed as an isolated final-stage operation, the proposed approach considers quality control as a continuous digital process throughout the manufacturing cycle. The integration of artificial intelligence, computer vision, digital identification technologies, programmable logic controllers (PLCs), sensors, industrial communication networks, and automated actuators creates a closed-loop quality-management environment. One of the most important findings of the study is that automated defect detection should not be considered independently from product identification and physical product management. A conventional computer-vision system may successfully determine that a particular product contains a defect; however, this information has limited practical value if the system cannot reliably associate the detected defect with the corresponding physical product and subsequently remove or redirect that product. The proposed architecture addresses this limitation by connecting the output of the AI-based inspection module with a unique product identifier and a real-time tracking mechanism. The integration of digital identification with quality assessment provides an important improvement in

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product traceability. Each product can be assigned a unique identifier through technologies such as QR codes, Data Matrix codes, RFID tags, or other identification mechanisms. Once the product passes through the inspection station, its quality status can be linked to the corresponding identifier. Consequently, the system can create a digital record containing information about the product, production batch, manufacturing time, inspection result, defect type, confidence level, and subsequent routing decision. This approach is particularly important for manufacturing environments in which product traceability is essential. If a quality problem is discovered after production, the digital history can help determine when and where the product was manufactured and which production batch it belongs to. Therefore, the proposed system can support not only real-time quality control but also post-production analysis and quality auditing. Another significant aspect is the use of artificial intelligence for automated defect detection. Traditional image-processing techniques can perform effectively under stable and controlled conditions, but their performance may decline when product appearance, illumination, orientation, or background conditions change. AI-based methods, particularly deep-learning models, provide greater flexibility because they can learn complex visual patterns directly from training data. The effectiveness of AI-based inspection, however, depends strongly on the quality and diversity of the training dataset. A model trained using a limited number of defect types may not perform reliably when previously unseen defects occur. Therefore, the development of a representative industrial dataset should be regarded as one of the most important requirements for practical implementation. The dataset should contain variations in lighting, product orientation, surface appearance, production batches, defect size, and defect severity. The problem of rare defects is especially important. In many manufacturing processes, defective products represent only a small proportion of total production. As a result, obtaining sufficient examples of every defect type can be difficult. This creates a class-imbalance problem and can negatively affect model performance. To address this issue, data augmentation, transfer learning, semi-supervised learning, self-supervised learning, and anomaly-detection methods can be considered. The discussion also indicates that model accuracy alone is insufficient for evaluating the effectiveness of the proposed system. In a manufacturing environment, false positive and false negative predictions have different economic and operational consequences. A false negative occurs when a defective product is incorrectly classified as acceptable. This can be particularly serious because the defective item may continue through the production process or reach the customer. A false positive, on the other hand, occurs when a good product is incorrectly classified as defective, potentially increasing waste and unnecessary rework. Therefore, quality-assessment systems should be evaluated using several complementary indicators, including accuracy, precision, recall, F1-score, false-positive rate, false-negative rate, processing time, and sorting accuracy. In addition, economic indicators such as waste reduction, rework reduction, labor savings, and return on investment should be considered when evaluating the practical value of the system. Real-time performance represents another critical factor. The proposed system is intended for manufacturing lines where products may move continuously at relatively high speeds. Consequently, detecting a defect is only one part of the problem. The system must also determine the position of the corresponding product and activate the sorting mechanism at the correct moment.

The relationship between conveyor speed, inspection-to-actuator distance, and system response time can be represented by:

$$t_a = \frac{L}{V}$$

where L represents the distance between the inspection point and the actuator and V represents conveyor velocity.

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The total response time of the system can be expressed as:

$$t_{total}=t_{capture}+t_{processing}+t_{decision}+t_{communication}+t_{actuation}$$

For reliable operation, the total system response time should remain lower than the product travel time:

$$t_{total}<t_a$$

This relationship demonstrates that increasing conveyor speed without optimizing the AI model and control architecture can result in incorrect sorting. Therefore, system designers must consider both AI accuracy and computational latency.

The integration of PLC technology provides an effective mechanism for translating AI decisions into physical actions. The AI model performs the analytical function, while the PLC coordinates sensors, timing, conveyor movement, and actuators. This separation between intelligent analysis and industrial control can improve system reliability and make the proposed architecture compatible with existing manufacturing infrastructure. For example, when the AI model identifies a product as defective, the corresponding decision can be transmitted to the PLC. The PLC then calculates or receives the required timing information and activates a pneumatic cylinder, robotic mechanism, servo-driven diverter, or other actuator. The defective product is subsequently directed to a rework station, inspection area, or rejection container.

This creates a closed-loop control structure:

Product → Identification → Image Acquisition → AI Analysis → Quality Decision → Tracking → PLC → Actuator → Product Routing.

Such an architecture represents an important transition from passive quality inspection to active quality management.

Another important finding concerns the integration of IoT technologies. Sensors installed throughout the production environment can provide additional information about conveyor speed, equipment condition, temperature, vibration, production volume, and other process parameters. When these data are combined with product-quality information, manufacturers can identify relationships between process conditions and defect occurrence. For example, an increase in surface defects during a particular period may be associated with abnormal machine vibration, temperature changes, tool wear, or incorrect process parameters. Therefore, historical quality data collected by the proposed system can become a valuable source for predictive analytics. This creates an opportunity to extend the system from defect detection toward predictive quality management. The development can be conceptualized as:

Defect Detection → Defect Classification → Defect Management → Defect Prediction → Defect Prevention.

Such a progression is consistent with the objectives of smart manufacturing and zero-defect production. The use of edge computing can further improve the proposed system. In conventional cloud-based architectures, images may need to be transmitted to a remote server for analysis. This can introduce communication delays and increase network requirements. In contrast, edge AI enables data processing close to the production equipment. As a result, image processing and decision-making can be performed with lower latency. The combination of edge computing and industrial control is particularly beneficial for high-speed production lines. A possible implementation can use the following structure:

Industrial Camera → Edge AI Device → PLC → Actuator.

This architecture minimizes unnecessary data transmission and enables rapid local decision-making.

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Despite these advantages, the proposed system has several limitations. First, AI models may require substantial computational resources, particularly when high-resolution images and complex deep-learning architectures are used. Second, changes in production conditions may cause model degradation. Third, the integration of heterogeneous industrial devices can create communication and interoperability challenges. Fourth, continuous model updating requires an appropriate data-management strategy. Cybersecurity is another important consideration. The proposed architecture connects cameras, AI systems, databases, PLCs, sensors, and industrial networks. Unauthorized access to these components could potentially affect both production data and physical manufacturing operations. Therefore, secure communication protocols, authentication mechanisms, network segmentation, access control, and system monitoring should be incorporated into practical implementations. The economic implications of the proposed system should also be considered. Although the initial implementation requires investment in cameras, computing hardware, identification devices, PLCs, sensors, actuators, software, and system integration, these costs can potentially be offset by reductions in defective-product leakage, manual inspection labor, rework, material waste, and production interruptions. The proposed architecture is also scalable. A small manufacturing line may initially implement only camera-based inspection and automatic rejection. As the digital infrastructure develops, RFID or QR-based identification, centralized databases, IoT sensors, edge computing, robotic sorting, and predictive analytics can be added. This makes the system suitable for gradual digital transformation rather than requiring complete replacement of existing production infrastructure. From a scientific perspective, the major contribution of the proposed approach lies in the integration of three traditionally separate functions: quality assessment, digital product identification, and automatic physical management. Existing research has made substantial progress in AI-based defect detection, but practical manufacturing systems require a stronger connection between digital decisions and physical product movement. The proposed system addresses this gap by establishing a direct relationship between the product's digital identity, AI-generated quality assessment, and automated routing decision. Therefore, the system can be considered not merely a defect-detection mechanism but an integrated intelligent quality-management platform. Future research should focus on experimental validation of the proposed architecture using real manufacturing datasets and physical production equipment. Particular attention should be given to the comparison of different AI architectures, including CNN-based classifiers, YOLO-based detectors, segmentation networks, and anomaly-detection models. The influence of conveyor speed, lighting conditions, defect size, camera resolution, and product orientation should also be experimentally evaluated. Further studies should investigate the integration of explainable AI methods to increase operator confidence in automated decisions. Explainable models could provide visual indications of the regions responsible for a defect classification, allowing engineers to verify whether the AI system has made a technically justified decision. Overall, the discussion confirms that the development of intelligent manufacturing quality systems requires a shift from isolated inspection toward integrated, real-time, data-driven control. The combination of AI-based visual inspection, digital identification, product tracking, PLC control, and automatic sorting provides a strong technological foundation for this transition. Such systems can improve manufacturing transparency, increase quality consistency, reduce human-related errors, and create new opportunities for predictive and autonomous production management.

Conclusion. This study presented an integrated system for product quality assessment, digital identification, and automatic management of defective products during the manufacturing process. The proposed architecture combines artificial intelligence, computer vision, digital identification, sensors, PLC-based control, industrial communication, and automated actuators into a unified cyber-

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physical manufacturing system. The main contribution of the proposed approach is the integration of three traditionally separated functions: quality assessment, product identification, and automatic product management. The system not only determines whether a product meets predefined quality requirements but also associates the inspection result with a unique digital identity and automatically determines the subsequent physical route of the product. The proposed mathematical framework demonstrates that reliable automatic sorting depends on the relationship between conveyor speed, the distance between the inspection point and actuator, and the total system response time. Therefore, real-time performance should be considered an essential design criterion together with classification accuracy. The integration of digital identification improves product traceability and enables the creation of detailed digital quality histories. This information can support production analysis, defect-source identification, quality reporting, and future predictive-quality applications. Despite its advantages, the system requires further research in several areas, including large-scale industrial datasets, rare-defect detection, domain adaptation, edge AI, explainable AI, cybersecurity, and adaptive model updating. Future research should focus on the experimental implementation of the proposed architecture in a real manufacturing environment and on quantitative evaluation using accuracy, precision, recall, F1-score, processing latency, sorting accuracy, false rejection rate, and economic efficiency. Overall, the proposed system provides a technological foundation for intelligent quality management and represents a promising approach to the digital transformation of manufacturing processes. Its implementation can contribute to improved product quality, enhanced traceability, reduced human error, lower production losses, and the development of smart manufacturing systems oriented toward zero-defect production.

References

1. Bishop, C. M., & Bishop, H. (2024). *Deep Learning: Foundations and Concepts*. Springer.
2. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
3. Kusiak, A. (2018). Smart manufacturing. *International Journal of Production Research, 56*(1–2), 508–517.
4. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*, 436–444.
5. Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters, 3*, 18–23.
6. Ma, Y., Yin, J., Huang, F., et al. (2024). Surface defect inspection of industrial products with object detection deep networks: A systematic review. *Artificial Intelligence Review, 57*, 333.
7. Nahar, L., Awrangjeb, M., & Islam, M. S. (2026). AI-enabled defect detection in industrial products: A comprehensive survey, key insights and future research challenges. *Advanced Engineering Informatics, 69*, 104067.
8. Qin, J., Liu, Y., & Grosvenor, R. (2016). A categorical framework of manufacturing for Industry 4.0 and beyond. *Procedia CIRP, 52*, 173–178.
9. Russell, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
10. Szeliski, R. (2022). *Computer Vision: Algorithms and Applications* (2nd ed.). Springer.
11. Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. *Journal of Manufacturing Systems, 48*, 157–169.
12. Zheng, X., Zheng, S., Kong, Y., & Chen, J. (2021). Recent advances in surface defect inspection of industrial products using deep learning techniques. *The International Journal of Advanced Manufacturing Technology, 113*, 35–58.
13. *Deep CNN-Based Visual Defect Detection: Survey of Current Literature*. (2023). *Computers in Industry, 148*, 103911.

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

14. *AI and Computer Vision-Based Real-Time Quality Control: A Review of Industrial Applications*. (2024). *Procedia Computer Science, 231*, 212–220.
15. *Machine Learning-Powered Vision for Robotic Inspection in Manufacturing: A Review*. (2026). *Sensors, 26*(3), 788.