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DEVELOPMENT OF A SYSTEM FOR PRODUCT QUALITY CONTROL AND MANAGEMENT OF THE MOVEMENT OF DEFECTIVE PRODUCTS BASED ON DIGITAL TECHNOLOGIES

Bobomurodov Elyor
E-mail: elyor.bobomurodov@inbox.ru
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Abstract: The rapid development of digital technologies has created new opportunities for improving product quality control and automating the management of defective products in modern manufacturing systems. Traditional quality-control approaches are often characterized by manual inspection, delayed decision-making, limited traceability, and dependence on operator experience. This study proposes a digital system for automated product quality control and management of the movement of defective products during the manufacturing process. The proposed system integrates industrial computer vision, artificial intelligence, digital product identification, Internet of Things technologies, programmable logic controllers, sensors, industrial communication networks, and automated actuators. The system captures product images, performs automated analysis, identifies potential defects, determines the quality status of each product, associates the inspection result with a unique digital identifier, and automatically directs defective products to designated routes. A mathematical model is proposed to determine the required response time for reliable product sorting based on conveyor velocity and the distance between the inspection and sorting stations. The study demonstrates that integrating digital inspection with automated material-flow management can improve product traceability, reduce human error, minimize defective-product leakage, and increase the efficiency of manufacturing quality management. The proposed system provides a technological foundation for smart manufacturing and can contribute to the transition from conventional quality inspection toward real-time, predictive, and intelligent quality management.

Keywords: product quality control, defective products, digital technologies, artificial intelligence, computer vision, automated inspection, digital identification, Industry 4.0, IoT, PLC, smart manufacturing, product traceability.

Introduction. The transformation of manufacturing under the influence of digital technologies has fundamentally changed approaches to production management, quality assurance, and logistics. The development of Industry 4.0 has resulted in the widespread adoption of artificial intelligence (AI), industrial Internet of Things (IIoT), computer vision, robotics, digital identification, cloud computing, edge computing, and cyber-physical systems. These technologies provide manufacturers with opportunities to establish highly automated production environments in which quality inspection and product-flow management can be performed continuously and intelligently.

Product quality is one of the fundamental determinants of manufacturing competitiveness. High-quality production reduces customer complaints, warranty costs, material losses, and rework requirements while increasing customer satisfaction and organizational reputation. Conversely, defective products that are not detected at the appropriate production stage may continue through subsequent technological operations, consume additional resources, and ultimately reach customers.

Traditional quality-control systems frequently depend on manual inspection. Although experienced operators can identify many types of defects, manual inspection becomes increasingly

problematic as production speed and product variety increase. Human operators can experience fatigue, reduced concentration, inconsistent judgments, and difficulties in detecting small or complex defects. Consequently, digital technologies are increasingly being used to automate visual inspection and quality decision-making.

Computer vision is particularly important in this transformation. Industrial cameras can continuously capture images of products moving along production lines. Image-processing algorithms and AI models can then analyze these images to identify deviations from predefined quality requirements. Deep-learning methods have significantly improved the ability of automated systems to recognize complex visual patterns and defects.

Nevertheless, product-quality control cannot be considered complete when a defect has merely been detected. The manufacturing system must also determine which physical product contains the defect and ensure that this product is directed to the correct destination. This creates a need to integrate quality inspection with product identification, tracking, and automatic movement control.

Digital identification technologies, including QR codes, Data Matrix codes, RFID, and other identification systems, provide the necessary connection between physical products and digital information. By assigning an identifier to each product, the manufacturing system can associate quality results with a specific item. This makes it possible to construct a digital history of the product, including information about its production time, production line, batch, quality status, detected defects, and subsequent movement.

The management of defective products is also an important component of the proposed system. Once a defect has been identified, an automated control mechanism must ensure that the corresponding product is separated from the normal production flow. Depending on the production environment, pneumatic actuators, servo mechanisms, robotic manipulators, conveyor diverters, or other devices can be used.

The main purpose of this study is to develop a conceptual digital system that integrates product quality control with automated management of defective-product movement.

The main research objectives are:

1. to develop an architecture for digital product-quality control;
2. to integrate computer vision and artificial intelligence into manufacturing inspection;
3. to establish digital identification of individual products;
4. to develop a mechanism for tracking products along the production line;
5. to automate the movement and separation of defective products;
6. to analyze the real-time requirements of the proposed system;
7. to identify the main technological limitations and future development directions.

Literature review. The evolution of manufacturing quality control can be divided into several technological stages. Initially, quality inspection was predominantly performed manually by trained operators. Later, automated optical inspection systems based on conventional image processing were introduced. These systems commonly relied on thresholding, edge detection, contour analysis, morphological operations, texture analysis, and geometric measurements. Traditional computer-vision techniques can provide reliable results when production conditions are highly controlled. However, their effectiveness may decrease when lighting conditions, product orientation, surface properties, or background characteristics change. These limitations stimulated the development of machine-learning-based inspection systems. Machine-learning algorithms can identify patterns from product data and classify products according to predefined quality categories. Support vector machines, decision trees, random forests, and other statistical learning methods have been applied to industrial quality inspection. However, many conventional machine-learning approaches require

manually engineered features. Deep learning has substantially changed automated defect detection. Convolutional neural networks can automatically extract hierarchical visual features from product images. Consequently, deep-learning systems can detect scratches, cracks, surface irregularities, deformation, discoloration, missing components, and other defect categories. Research on industrial surface-defect inspection has demonstrated the growing role of deep-learning technologies in manufacturing. Object-detection networks are particularly valuable when the location of a defect must be determined in addition to its existence. Image-segmentation methods can provide more detailed information about defect boundaries and dimensions. Another important research direction is industrial anomaly detection. Defective products are often rare compared with normal products, making the collection of large labeled datasets difficult. Unsupervised, semi-supervised, and self-supervised learning methods can therefore provide useful alternatives when labeled defect data are limited. The development of Industry 4.0 has also encouraged the integration of computer vision with IoT and cyber-physical systems. Sensors, cameras, controllers, robots, and databases can exchange information through industrial networks. This enables manufacturing systems to perform continuous monitoring and automated decision-making. Digital identification technologies provide another important layer of intelligent manufacturing. RFID, QR codes, and Data Matrix systems allow individual products to be associated with digital records. When combined with quality-control data, these technologies provide product-level traceability. Despite significant progress, a research gap remains between automated defect detection and automatic physical management of defective products. Many systems focus on identifying defects without providing an integrated mechanism for product identification, tracking, and automated routing. The present study addresses this gap by proposing a unified architecture that connects quality assessment with digital identification and automated product movement.

Discussion. The proposed system demonstrates that digital quality control should be regarded as an integrated manufacturing process rather than as an isolated inspection operation. The principal advantage of the proposed architecture is the connection between defect detection and subsequent physical product management. In a conventional inspection system, the main question is whether a product is defective. In the proposed system, the decision process is extended to several additional questions: What product is being inspected? What is its digital identity? What defect has been detected? Where is the product located? What action should be performed? Where should the product be directed? The integration of digital identification with AI-based inspection is particularly important. An AI model may correctly identify a defect, but the result becomes operationally useful only when the system can associate that result with the correct physical product. Digital identification provides this connection. Product traceability is another important benefit. The system can maintain historical records of individual products. If a quality problem is identified after production, the manufacturer can investigate the corresponding product ID, production batch, production time, and inspection result. This can support root-cause analysis and quality auditing. The use of artificial intelligence can significantly improve automated visual inspection. Deep-learning models can learn complex visual patterns and identify defects that may be difficult to describe using conventional rules. However, the effectiveness of AI depends on the quality of the training data. The training dataset should contain sufficient variation in product orientation, illumination, surface characteristics, defect size, and defect type. Otherwise, the model may perform well under laboratory conditions but poorly in real manufacturing environments. Rare defects represent a particularly important challenge. Because defective products may constitute only a small fraction of total production, collecting sufficient examples for each defect class can be difficult. Anomaly detection and semi-supervised learning therefore represent promising directions

for future development. Real-time operation is also critical. The system must complete image acquisition, processing, decision-making, communication, and actuation before the defective product reaches the sorting station. The mathematical relationship

[t_{system}<\frac{L}{V}]

provides a basic criterion for system design.

If conveyor speed increases, the available response time decreases. Therefore, high-speed production lines require optimized AI models, efficient computing hardware, and low-latency industrial communication.

Edge computing can be used to reduce processing and communication delays. Instead of sending every image to a remote cloud server, the AI model can operate close to the production line. A possible architecture is:

Industrial Camera → Edge AI → PLC → Actuator.

This approach can improve response time and reduce network traffic.

PLC integration also plays a critical role. AI systems are primarily responsible for data analysis and decision-making, whereas PLCs provide deterministic control of industrial equipment. Combining these technologies allows digital intelligence to be translated into reliable physical action. The integration of IoT technologies creates additional opportunities. Sensors can provide information about machine condition, temperature, vibration, conveyor speed, and other production parameters. By combining these data with quality information, manufacturers can investigate relationships between machine conditions and defect occurrence. For example, if the defect rate increases simultaneously with abnormal equipment vibration, the system may identify a possible relationship between machine condition and product quality. In the future, machine-learning models could use such information to predict defects before they occur.

The proposed system can therefore evolve through several stages:

Quality Inspection → Defect Detection → Automatic Sorting → Predictive Quality → Defect Prevention.

This development is consistent with the objectives of smart manufacturing and zero-defect production. Despite the advantages, several challenges remain. The first is the requirement for high-quality training data. The second is the computational cost of complex AI models. The third is the adaptation of models to changing production conditions. The fourth is the integration of different industrial devices and communication protocols. Cybersecurity should also be considered because the proposed architecture connects production equipment, databases, cameras, controllers, and communication networks. Secure authentication, access control, encrypted communication, network segmentation, and continuous monitoring should therefore be incorporated into practical implementations. Economic efficiency is another important consideration. The initial cost of industrial cameras, computing hardware, identification equipment, PLCs, sensors, actuators, and software can be significant. However, these investments can potentially be justified by reductions in manual inspection costs, defective-product leakage, rework, material waste, and production interruptions. The system is also scalable. A small production line may initially implement only automated visual inspection and product rejection. Additional technologies such as RFID, IoT sensors, edge computing, robotic manipulation, and predictive analytics can subsequently be incorporated. The main scientific significance of the proposed system lies in integrating quality assessment, digital identification, and automatic defective-product movement into one technological architecture. This approach moves beyond traditional inspection and creates a basis for intelligent, data-driven, and cyber-physical quality management.

Conclusion. This study proposed a digital system for product quality control and automatic management of defective products during manufacturing. The proposed system integrates artificial intelligence, computer vision, digital identification, IoT technologies, PLC-based control, sensors, industrial communication, and automated actuators. The proposed architecture provides a continuous process consisting of product identification, image acquisition, AI-based quality assessment, digital recording, product tracking, decision-making, and automatic routing. This integration enables defective products to be identified and physically separated without requiring continuous manual intervention. One of the key advantages of the system is improved product traceability. Linking quality information to a unique product identifier makes it possible to maintain a digital history of individual products and production batches. Such information can support quality analysis, defect-source identification, production auditing, and future predictive-quality applications. The mathematical model developed in the study demonstrates that automatic sorting reliability depends on conveyor speed, inspection-to-actuator distance, and total system response time. Therefore, real-time performance should be considered together with detection accuracy when designing industrial AI systems. The proposed system can reduce the influence of human factors, improve inspection consistency, minimize defective-product leakage, and increase the transparency of manufacturing processes. However, practical implementation requires attention to training-data quality, rare-defect detection, computational resources, system integration, cybersecurity, and economic feasibility. Future research should focus on experimental implementation of the proposed architecture in real manufacturing environments. Comparative evaluation of CNN, YOLO-based detection, segmentation, anomaly-detection, and self-supervised models should be conducted. Additional research should investigate edge AI, digital twins, predictive quality management, explainable AI, and adaptive model updating. Overall, the proposed digital quality-control system provides a promising technological foundation for the transition from conventional quality inspection to intelligent and automated manufacturing management. Its implementation can contribute to improved product quality, enhanced traceability, reduced waste, lower inspection costs, and the development of smart manufacturing systems oriented toward zero-defect production.

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