Real-Time Statistical Process Control and Root Cause Intelligence: AI-Driven Quality Assurance Systems for U.S. Manufacturing Revitalisation

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1. Introduction to AI-Driven Quality Control Systems, Manufacturers across the globe consistently seek profitable opportunities to bolster their business and competitive edge. Emerging markets in developing countries with low labor costs and rapid rates of industrialization are establishing manufacturing operations and industries. To compete in terms of product quality and variety, of the developed nations, manufacturers must adapt to industry 4.0 and focus on a broader implementation of Artificial Intelligence (AI) and Intelligent Manufacturing Systems in quality control systems and other processes [1]. However, globally, only 7% of all companies have begun implementing AI. One of the main hurdles for adoption is the expense, complexity, and lack of AI expertise for implementation. A more general, flexible, and affordable AI option for adapting advanced AI technology to the quality control of processes in a factory is presented.

An AI-based supervisory quality control system for manufacturing processes is developed to benefit small and medium-sized manufacturers and be independently developed and maintained by them [2]. Conventional quality control systems typically involve a significant monitoring burden on human supervisors, who must discard the obvious defect products and monitor the machines in parallel. The developed system can significantly improve the effectiveness of human supervisors in relevant manufacturing scenarios, thus improving productivity and reducing labor costs. Five different AI modules for the smart supervision of features related to images, the magnitude of variables, and similarities are developed. The AI modules can be combined in various ways for different processes, thus forming a flexible and customizable system.

2. Foundations of AI in Quality Control

Laying the groundwork for understanding AI-driven quality control systems focuses on the fundamental concepts of machine learning and deep learning. There are different types of traditional machine learning models, and two successful vision-based quality control inspection systems are presented as representative examples of moving toward AI-driven systems. The foundation of modern AI is ascribed to the emergence of deep learning models, with a simple explanation of how a well-known architecture, the convolutional neural network, works. To understand AI-driven quality control systems, basic concepts or background in machine learning and deep learning are required [4].

2.1. Traditional Machine Learning Models

A simple, generally used, and understandable graphic representation is introduced to describe the traditional machine learning model. Conventional computer vision-based machine learning models consist of three major components: a feature extraction block, a classifier block, and non-detection output processing [5]. The input to such traditional machine learning systems is a one-dimensional matrix or a set of discrete broken features from 2D images. Detected broken features are then fed to one out of many compared classifiers, such as the support vector machine model, k-nearest neighbor model, random forest model, and so on. Lastly, the output is processed for decisions on many cases, such as “pass,” “fail,” or “discard.”

The first moving-case inspection system is designed based on a traditional machine learning model. The concept of a QC drone-like system inspection is implemented at the production line for the quality evaluation of moving camera lenses assembled with multiple components. The drone-mounted camera captures the images of the sample lens from four angles to extract the inserted focusing lens feature information. Each captured image goes through the built-in traditional machine learning model with the support vector machine classifier and is finally evaluated as “acceptable” or “not acceptable” based on pre-set criteria.

The second vision-based inspection system presented is for judging the grading of surface-defect levels in chips. The built-in traditional machine learning model is designed based on the pre-extracted three different features: the local binary pattern feature, the histogram of oriented gradients feature, and the central symmetric local binary pattern feature. The good chips with surface defects are classified into five levels by the random forest classifier. Each model was trained separately with a specific defect, and deciding the defect classification is based on one output model with the maximum probability of accepting and classifying the defect.

2.1. Machine Learning and Deep Learning Basics

Owing to the proliferation of sensors, cost savings by using advanced process equipment, and recent breakthroughs in artificial intelligence (AI), the manufacturing sector is experiencing unprecedented improvements in practices and productivity. AI technology development and deployment in manufacturing offer several opportunities, including the conceptualization of the AI-driven smart factory. On a broader scale, AI augments almost all aspects of growing intelligence with enhanced safety, reliability, and robustness. In quality control (QC), the most mature and widely applied among industrial AI applications is automated visual inspection (AVI) [6]. AVI examines the comparative aesthetic quality of manufactured products using cameras and other computer vision systems and advanced learning algorithms as a substitute for human inspectors. It has the potential to drastically reduce production costs and time losses caused by scrap and reworks. In conjunction with more recent algorithmic advancements, such as those based on deep learning (DL) or convolutional neural networks (CNNs), AVI is expected to significantly improve the competitiveness, overall quality, and integrity of manufacturing enterprises. This section reviews the main principles of machine learning and deep learning.

Machine learning (ML) is a branch of artificial intelligence (AI) and encompasses a collection of data analysis techniques based on the idea that systems can learn directly from experience and automatically improve their performance. It consists of a set of algorithms capable of extrapolating patterns from historical data without being explicitly programmed [7]. Particular emphasis is placed on sophisticated supervised and unsupervised statistical learning algorithms mainly from the fields of artificial intelligence and statistics. Machine Learning (ML) is a rapidly growing domain of artificial intelligence (AI) that empowers computer systems to autonomously learn, adapt, and enhance their performance from historical data or direct experiential feedback. Within AI, ML signifies a broad assortment of data analysis methodologies predicated on the premise that systems can derive rules from their own experience. DL is a pioneering subset of ML that has garnered widespread recognition owing to its considerable triumph in high-dimensional complex data analysis predicaments.

3. Key Components of AI-Driven Quality Control Systems

The essential components of an AI-driven quality control system are elucidated in this section, focusing on sensors and data because this discussion is preliminary to understanding the practical things to make AI work in quality control. AI-driven systems for a manufacturing facility have two practical aspects: continuous data collection and analysis of the collected data with AI-tools [1]. Any quality control solution based on AI, whether general or industry-specific, requires data acquisition. The following discussion emphasizes acceptable sensor installations and data collection strategies.

Vision systems encompass one primary area for smart manufacturing systems in terms of denoting an acceptable system and its components. Numerous vision systems are already present in people's homes and workplaces, and their costs have been dwindling consistently. Vision systems consist of the camera itself (sensors) and data acquisition (computers capturing images) and processing systems. Vision systems act as a "human eye", which is paired with gathering knowledge to classify pictures using AI. People using cell phones are already utilizing a basic aspect of AI in terms of picture enhancement [2]. Manufacturing facilities already have a basic version of a vision system in terms of a "IR-safety light screen," although no intelligence is present in this simple implementation. As vision systems are the basis for smart manufacturing technologies in AI-driven quality control, there are some critical components needed for manufacturing plants.

3.1. Sensors and Data Collection

Sensor technologies play an indispensable role at different stages in the on-line quality control framework. As the most important component of the data collection, sensors detect and visualize the pre-processed information of underlying production processes or manufactured products based on physical principles, and these signals are taken as input for data pre-processing [2]. The characteristic features of collected data obtained from different kinds of sensors determine the performance of data fusion, fault detection algorithms, and tasks of data-driven anomaly detection. A synergistic effect between heterogeneous sensors is supposed to develop at the same time by on-line monitoring of physics-based, signature-based, soft-sensing, and other types of sensors.

Embedded sensors daintily fabricated on the same substrate as fabricated micro-devices, such as MEMS-knife-edge micro-machined structures, take advantage of the temperature signature of laser heating and fast test-time, leading to an efficient on-line quality control in the field. High-accuracy miniature sensors can be used to measure the vibration and dynamic features of CNC machines, producing abundant multi-domain data during operation conditions. The flexible and modularized design of sensors with a strategy of information consistency check mechanism is proposed based on exploring multi-dimensional and multi-domain characteristics of data [6] , which deals with the issues of heterogeneous data inconsistency and enhances data uncertainties.

4. Integration of AI with Traditional Quality Control Methods

The adoption of AI technologies has emerged as a formidable approach to enhance traditional quality control systems. However, the challenges associated with the convergence of AI with such quality control systems co-exist. This work explores the issues and benefits associated with the integration of AI to traditional quality control approaches. The implication of harmonizing AI with traditional quality control perspectives is presented. An insightful view of the opportunity and challenge regarding the integration of AI technologies into traditional quality control methods is provided [3].

Quality management systems are indispensable for manufacturers to ensure product quality compliance with given specifications and tolerances. Traditional quality management systems can be categorized into detecting, rejecting, and separating, which reactively address quality issues once they arise. Advanced approaches to quality management are necessary to reduce the burden on manufacturers and assure higher quality levels with fewer resources. Recently, researchers have emphasized the use of Artificial Intelligence (AI) to advance manufacturing systems, including quality control systems. AI technologies can technically be integrated into traditional quality control systems and subsequently advance them [4].

4.1. Challenges and Benefits

Artificial intelligence (AI) has potential as a quality control system for the revitalization of U.S. manufacturing. However, there are challenges to integrating AI with traditional quality control methods. These challenges include increased investment and labor costs, data availability, training and implementation, and a mindset change within organizations [8]. Quality control departments and their processes are sometimes considered cost centers and are less amenable to the introduction of expensive technology like AI. Additionally, organizations may be slow to embrace data-driven approaches, especially if pre-AI systems have performed adequately from a profit standpoint. Investments in human capital, such as training staff on new AI systems, also entail significant costs.

Despite these challenges, AI-driven quality applications hold the promise of sizable cost savings and value creation if they work effectively, leading some firms to put in place plans for trials and adoption [4]. By understanding the challenges posed to organizations hoping to integrate AI with existing quality methodologies, AI implementation can be robust and effective, setting firms up for positive outcomes. Ultimately, these benefits can help keep firms competitive in the manufacturing sector and the U.S. economy healthy.

5. Case Studies in AI-Driven Quality Control

[1]

Quality control using artificial intelligence (AI) has led to considerable improvements in product quality and productivity in the manufacturing industry. However, some work processes that require judgment and expertise are still performed by humans. Trimming die design inspection to minimize potential failures is one of these tasks and is still performed manually by engineers. Accordingly, the automatic design inspection of the trimming dies is a crucial challenge for automating the quality control process in the automobile industry. In this study, which is regarded as an initial effort to solve the challenge, a new design inspection system for automobile trimming dies is developed by integrating AI modules and computer-aided design (CAD) software used in the industry. The AI modules replace the human engineers' judgment of design inspection rules and the CAD software performs the operations requested by the AI modules. The design inspection task is completed through a zigzag interaction between the AI modules and CAD software by a one-click operation without the intervention of the experts. The AI modules are designed to be CAD-independent and data-efficient; therefore, they can be easily adapted to other CAD software and achieve high performance, even when trained with only a few trimming dies. In addition, the inspection time is reduced to approximately one-fifth of the manual inspection time by experts.

[4]

There are numerous applications of Artificial Intelligence (AI), Machine Learning (ML), and other automated decision systems in today's world. The impact of AI/ML systems can be positive, neutral, or detrimental, depending on aspects like intent, selection and application of algorithms, and interpretation of system output. In general, the use of an AI component has one of three goals: (1) delegation of tasks traditionally accomplished by human beings, (2) augmentation or support of human activity or interpretation, or (3) enhancement of information retrieval and access capabilities. Thus, from the system or software management point of view, it has all the same expectations as any other software component. Such expectations include but are not limited to exigencies for the engineering and operation of software, such as documentation, responsibility, internal control, troubleshooting, predictions, efficiency, sustainability, quality, and risk management applicable to any software component. The utility of the basic structure is immediately evident, and in consideration would be added the system or software-specific objectives, such as attaining an acceptable level of trust in the correctness of operation.

5.1. Automotive Industry

Automobiles are complex products composed of numerous parts, and the quality control of their interior panels is significant because plastic lids are commonly used for aesthetic design. Quality control was performed manually by skilled experts using a two-dichroscope-based frenzy inspection method, which is difficult to implement in a competitive manufacturing environment. An automatic defect detection algorithm is introduced, which adopts traditional illumination and imaging principles and CNN-based machine learning techniques. The design defects and how to detect them, including waviness, bulging, wrinkles, and oil stains, are explained. To automatically detect the above mentioned defects, an end-to-end automatic defect detection algorithm is established based on five modules and detection processes. The modules are classic image processing techniques for illuminating enhancement, noise filtering, edge detection, contour detection and approximation, and CNN-based classification. A product part is defined in an approximate oval region for efficient geometric detection. Two ways of capturing images and an example of defect detection are shown [1].

To adopt AI in the automobile industry, it is critical to either collect a good amount of training data or find a system that already had a similar learning background. A CAD-independent AI-driven design inspection workflow with good generalizability is proposed, which can detect design errors, save inspection time and human resources, and is easy to use. The proposed zigzag interaction was evaluated at a Korean automotive part manufacturer with an inspection task of trimming dies, and this batch type was chosen because a trimming die can cost more than the price of a vehicle. Building variants of AI modules requires expertise, which a firm with little experience in AI may find challenging. If several CAD and AI modules were created for geometries with similar features, they could be used as a base for learning and building AI modules. Automobiles include parts with a variety of geometric features, such as air ducting, exterior design trim panels, interior design trim panels, and structural parts. The level of conformity to the CAD of these parts can be controlled through settings in the proposed inspection workflow [4].

6. Ethical and Regulatory Considerations in AI-Driven Quality Control

As AI systems begin to outperform humans in areas such as diagnosis, detection, and prediction tasks before they go wrong, the ethical consideration of AI utilization in quality control starts to gather pace. In some respects, this is no different from the development of any other multi-million designing, building, and operating technology. Negative externalities like job loss, financial loss, technical malfunctions, etc., emerge, and so do guidelines for AI accountability, transparency, robustness, and fairness [3].

As AI systems gather data built-in systems, it encroaches on privacy and data protection, especially when processing biometric data like fingerprints or Digital Non-Retrievable Stamp (DNRS). It is suggested to conduct a privacy impact assessment before an AI solution implementation and ensure compliance with privacy legislation (each member state of the EU has to appoint a national data protection authority responsible for the enforcement and implementation of the General Data Protection

Regulation). Digital ID can shield an individual from potential data misuse or bias ripple effects during life transformation [4].

Another framework is the AI Act, with the objective to ensure that the use of EU's artificial intelligence is safe and respectful of existing laws on fundamental rights and Union values. The act does not target the technology itself; instead, it aims to govern the use of specific AI applications, classifying AI systems according to risk categories and setting requirements and obligations accordingly.

7. Conclusion

The ever-increasing competition and globalization continuously challenge the manufacturing sector. While strategically leveraging AI for operations is likely to strengthen the U.S. manufacturing industry against its global counterparts, the nature of AI developed by and employed in manufacturing is a systemically and societally complex issue. Applying AI in manufacturing systems comes with significant social, ethical, and practical implications. These broad issues arise from or are exacerbated by the nature of manufacturing itself and the AI technologies being applied to it. Similarly, efforts to strategically leverage AI in manufacturing fail to fully articulate the potential impact on labor, both now and in the future, such analyses primarily focus on productivity and economic competitiveness [8].

The need for an ongoing national dialogue over AI's broader and longer-term societal implications is made even more urgent in light of manufacturing's dramatic shifts in the workforce and productivity over the last several decades. Unlike other industries that became largely automated and globalized in the latter half of the 20th century, significant innovation in manufacturing technologies and operations methods that increasingly leverages AI and digitally connected systems are just now being introduced and adopted. It is in this context that deliberate thought and action regarding the social, ethical, and practical implications of AI technologies on manufacturing, and in turn broader social systems, is urgently needed. Therefore it is hoped that the insights, concerns, and questions presented will serve as a starting place for an ongoing and nationwide dialogue over the societal implications and consequences of AI applications and developments in manufacturing.

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