In-Line Sensor Fusion and Predictive Quality Modelling: AI-Driven Quality Control Frameworks for Revitalising U.S. Manufacturing Operations

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1. Introduction, What is an AI-driven quality control system? Why is AI-driven quality control critically significant in revitalizing U.S. manufacturing?

The AI-driven quality control system (AI-QCS) consists of an interaction of intersystem complementary components and is optimal in maximizing the cyber-physical system. The AI-driven quality control system (AI-QCS) comprises not only hardware, including sensors, actuators, embedded systems, and robots, but also intelligent software performing various functions in closed-loop mode.

In the AI-IoT era and Fourth Industrial Revolution, AI and machine learning, big data, IIoT, cloud manufacturing, edge computing, cyber-physical system, digital twin, and various advanced technologies are widely applied and integrated with each other to establish and maintain AI-driven smart manufacturing systems with superior performance attributes. AI-driven quality control for enhancing product quality requires the insertion of suitable methods and the adaptation of functionalities inside the simple (dedicated hardware-based and simple algorithm-based) quality control functions used in classic manufacturing and automated inspection systems.

This paper aims to present AI-driven quality control systems for revitalizing U.S. manufacturing. The technical trends, key technologies, and state-of-the-art of AI-driven quality control are comprehensively discussed. The innovation of AI-QCS is highlighted, and its applications are explained in detail. The realization of AI-QCS is smart, adaptive, and self-driving AI-IoMT systems. The systems also include other synergistic CCS-components, such as quality model, sensing technology (hardware), IIoT sensing system (hardware), 5G/6G communication technology, cloud computing, edge computing, digital twin, high-performance computing, IIoT network, logistics, and infrastructure, supply chain, customer demand, closed-loop feedback mechanism, advanced soft robotic system, security and safety subfunction systems, and virtual manufacturing and service environment.

1.1. Overview of AI in Manufacturing

Artificial intelligence (AI) and machine learning (ML) are changing the face of a variety of fields including agriculture, social media marketing, healthcare, and manufacturing. One of the most expected applications for ML in the future is the successful automation of the quality control (QC) process for high-volume production in manufacturing. ML could solve the challenges posed by older methods of QC and reduce cost while maintaining or improving on product quality. AI in manufacturing has seen a notable increase in research and is used to improve processes in the following areas: machine maintenance, equipment maintenance, optimization based on product or process information, maximizing power usage, demand prediction, response to next product offerings from consumers, and automation in the design ecosystem.

The introduction of new technologies such as IIoT also has driven change from conventional production scheduling, called push manufacturing, to more adaptive and change-driven managerial techniques, called pull manufacturing. As a result, lean production based on the pull manufacturing model has been increasingly adopted by global manufacturers. AI and machine learning in manufacturing has also seen strong growth in industry 4.0, promoting the trend of smart manufacturing. Quality management has been a continuing focus in general, and the focus of work in the area is shifting to ways that AI can integrate into these other applications. Therefore, this paper focuses on discussing the innovations and applications of AI in automated QC in manufacturing, with specific attention paid to the subfield of material processing.

2. Challenges in Traditional Quality Control

Traditional quality control (QC) methods have played a critical role in ensuring product quality and have been used at various stages of production for many decades. However, traditional QC methods and approaches have some intrinsic limitations. Generally speaking, monitoring and diagnosis based on human operators involved qualitative judgments and usually require a substantial amount of time to conduct. Moreover, inspection and sampling strategy-based traditional QC approach has a relatively low detection rate for defective products, especially when it deals with unobservable defects in small components and hazardous environments where human inspectors and operators are normally discouraged. The manufacture of products with a low level of quality not only leads to significant economic losses but also, as important, damages the "Made in the US" brand. Last but not least, due to the aging demographics, the US now faces an imminent labor shortage in manufacturing. For these reasons, it is important to develop advanced manufacturing technologies and approaches that can improve the level of product quality, increase the processing efficiency and reduce the reliance on human labor, and the proposed AI-Driven Quality Control System is an effective way to address these challenges.

To address the limitations of traditional QC and related approaches and realize the promise of advanced industrial automation is to develop and establish an AI-driven quality control system for online and in-situ diagnostics and prognostics. The goal is to compare and contrast the proposed systems with existing technologies, and to identify best practices and areas for improvement associated with the proposed system through extensive collaborations with industrial partners. The proposed AI-driven quality control system will dramatically revolutionize the existing technology for online and in-situ QC, and will greatly increase the competitiveness of US manufacturers. With features of convenience, high-speed execution, high accuracy, low cost, and inference, the proposed AI-driven development will be the next game changer in the US manufacturing sector.

2.1. Limitations of Human Inspection

In quality control for manufacturing processes, human inspection is the last line of defense from delivering defective products to the customer. Oftentimes, human inspectors are responsible for manually inspecting the final product and are forced to make rapid decisions at high speed and efficiency with a range of products and instructions. From both a cost and performance perspective, the likelihood of human inspection making errors is high. In general, humans experience a high degree of inter-operator variability, attention modulation (i.e., lapses in attention, focus), operator fatigue, subjective bias, and are slow to adapt to novel objects and rapidly changing environments. Consequently, it is not uncommon for human inspection to produce false accepts or false rejects of good parts. When defective parts are produced with the potential of being delivered to end customers, the resulting product recalls and compensation are highly expensive in terms of product liability costs and damage to a company's name-brand.

Over the years, companies have used various statistical sampling methods in order to estimate the quantity of damaged (defective) products that reside in their lots, in order to manage their product warranties and pay compensation when implicated. In both the automobile and biotechnology industries, even with standard and complex test procedures, such as magnetic particle inspection, thermography, and volumetric inspections, it is often the responsibility of the "human" inspector to make final adjudication of an automated system's output. It is no secret that human visual inspection may not be the optimal process to ensure the quality of products. Rather, integrating a robot with computer-based intelligent visual inspection can achieve a high degree of potential assessment to improve inspection, in furthering the capabilities of intelligent systems, i.e., a robotic system that is designed to recognize and join metal surfaces, which incorporates tactile feedback to reduce the gap between metals to 5 μm.

3. Role of AI in Quality Control

Vision quality control focuses on identifying defects (often with image processing algorithms or Video Enhanced manufacturing, VEm) for their subsequent identification and rectification. Traditionally, workers directly employed in the plant have eyeballed these parts for identification of defects and the defective parts are then identified for the rectification. However, the process has changed since 1973, when NEC engineers built a machine-learning algorithm into their computers that could identify pictures of cars with 20 cars in different angles and lighting conditions.

AI technologies have revolutionized the QC process. It helps in reducing costs and can thus help in bringing back some of the production from developing countries back to the US. AI has importance and significance in such a field as quality control where the demand is increasing. AI performs decisions that are based on the input data to create predictions. Inference is also performed by AI to determine the best actions and for optimization. These can provide decisions such as what division will make the product, what shift will produce the product, and also what equipment will produce the product. Also, they can provide predictions such as defect rates and maintenance requirements, and also optimization such as energy and other resources and also space. A study also shows a significant improvement in the process industries with increased intelligence, responsiveness, decision accuracy, and increased optimization by using AI. In this paper, we aim to discuss the ML algorithm used in AI-driven US manufacturing.

3.1. Machine Learning Algorithms in Quality Control

Machine learning algorithms, especially deep learning, have started to play an important role in developing highly efficient quality control systems. These algorithms can be employed to create numerous quality control solutions by directly processing sensory data or other monitoring data to identify the real quality states of the manufacturing parameters by automatically learning supervision from data. Machine learning algorithms can learn recognizable models from sensory data produced in the manufacturing process. These statistical models can be used to predict objectives and to compute interior states of the manufacturing in order to regulate processes for arriving at desired production results. It is then important to verify the learned models by using quality control concepts in order to evaluate the actual competences of the above-mentioned use of machine learning algorithms for manufacturing.

The principle of PCA conveys compactness in the way products ought to be qualitatively controlled for designating products as a part of conforming or non-conforming classes through a discrimination function. For the situation in which machine learning algorithms are used instead of the above-mentioned quality control concepts, these applications must be matched with basic statistical processes. Machine learning algorithms such as convolutional neural networks can fulfill this issue. Only then can the process of combined AI-driven quality control and individual AI-driven quality control be applied to the quality control management solutions of manufacturing. In addition, a promising future of combining AI-driven quality control and individual AI-driven quality control could be used in manufacturing. Figure 1 illustrates the first three components for Principal Components Analysis of date palm samples.

4. Key Innovations in AI-Driven Quality Control Systems

Some of the key innovations in contemporary AI-driven quality control systems abound in this growing area of research and application. The broad application of quality inspection using computer vision in many different sectors from automotive, aerospace, consumer electronics, agricultural machinery, and shipbuilding machinery, among many others, underlines the increased attention and utilization of AI in reshaping the manufacturing industry. Despite the remarkable proliferation of various sophisticated methodologies, many research challenges are identified, including the need for scalable quantitative evaluation techniques outside of competition scenarios to underscore the potential of many state-of-the-art methods being directly applied to applications at scale.

In recent years, quality inspection methods powered by AI, especially using computer vision and image recognition technologies, have attracted significant attention in both academia and industry. The success of AI-based quality control in a range of settings has significantly impacted and shaped the prevalence and adaptability of AI-driven quality control in various settings, not least in transforming a new paradigm for quality in the manufacturing industry. Many automatic quality inspection solutions have leveraged computer vision, i.e., extracting visual information from images or videos in seeking to automate routine tasks and improve accuracy. Recent works in quality inspection have looked at using methods established in computer vision for object detection and semantic segmentation. More complex systems with improved network architecture are, however, being increasingly used to facilitate the categorization and tagging of defects in images, as well as in video datasets. More sophisticated AI software architecture for quality inspection is furthermore being developed to leverage learning under multi-task environment settings and retain some level of robustness – as the interchange between multi-task settings complicate the training of defect detection systems in practice, rendering the software less robust than in controlled environments.

4.1. Computer Vision and Image Recognition

Vision and image understanding have significantly progressed in the past decade, and as a result, the performance of computer vision and image recognition has reached close to human levels for a range of tasks. In particular, convolutional neural networks (CNNs) are the backbone of almost all recent computer vision systems. These innovations in image understanding are essential for AI-driven quality control systems, as they set the foundation for cutting-edge systems that can be applied in manufacturing settings. Given recent progress, we can begin to discuss the application of these systems in an industrial setting, specifically on the shop floor of U.S. manufacturing businesses.

Computer Vision: The most instrumental technology required for DTQ is recent innovations in the field of computer vision. These algorithms can process a large number of images and relay high-quality results in real-time to shop floor workers in a manufacturing setting. These tools are likely to revolutionize the entire inspection industry. There were several objections to the idea that experts such as radiologists, pathologists, and dermatologists could be replaced by algorithms. Computer vision is at a point where it is becoming difficult to distinguish from human vision. It is estimated that moving forward, computer vision accuracy will surpass that of humans. This demonstrates the importance of integrating these new techniques into the U.S. manufacturing sector.

5. Applications of AI-Driven Quality Control in U.S. Manufacturing

Automotive industry implementations

As a leading indicator of U.S. manufacturing, the automotive industry has been an early adopter of AI-driven quality control technology. A dominant OEM, for example, has started using AI-driven quality inspection tool to improve productivity by reducing inspection times and costs. This OEM identifies unusual part features and performs additional inspection checks, leveraging the use of AI to help its people succeed in providing consumers with high-quality automobiles. After the many successful demonstrations, a leading T1 aerospace supplier in the U.S. has utilized Luminous Manufacturing's AI technologies to monitor parts at two of its facilities. By detecting anomalies early on with a dynamic threshold, the T1 engineer was able to monitor the process throughout the day from home. The automotive and aerospace parts sectors have difficulty accommodating failures because they often have a $2,000-5,000 sunk-cost when keying parts. Manufacturers are curious how visual AI technologies compare when designing a product to perform a 100% part inspection versus a visual AI designed to inspect a small set of key features found on the part.

Furthermore, AI-driven QC methods have been developed and implemented into T1 suppliers of global Fortune 500 automotive companies for automotive interior products. A wide variety of materials are used in automotive interiors, with a high variety of potential scratches and flaws. These defects are undetectable with traditional rule-based algorithms and can be easily missed by human inspectors. The use of AI-based inspection has made a significant decrease in the number of defective automotive parts, making them accessible to automotive safety regulators. One such example is a process for using our Shearwater toolkit to inspect airbag doors. In one case, the system's manufacturer detected a number of false-positives. The OEM asked if the supplier could modify the AI model so it only alerts the operator if at least four or more scratches with a minimum length of 20 pixels were found.

5.1. Automotive Industry

The AI-driven quality control (QC) technologies are appealing to American manufacturers to mitigate the above challenges and problems. One of the industries that witnessed successful application of AI-driven QC and quality improvement is the automotive industry. We will detail the application in this section.

In the automotive industry, vehicle defects, recalls, and other quality issues were taking decades to recognize through manual and traditional QC processes, but thanks to AI and machine learning (ML), adverse patterns began to reveal within a period of a single year after implementation. At the tier 1 level, automotive manufacturers began using an end-of-line automated auto vision inspection machine that utilizes AI to recognize any paint and body defects. An AI camera continuously learns from a growing data set of part variables and instantly sends feedback, alerting in case of an issue, and processing information into reports through the entirety of the car's assembly. Placing AI into a paint shop can offer another level of QC to distinguish, categorize, and sort problems for its resolution by human intervention or through an upgraded automated application utilizing sensors and robotics. An offline AI database, using new innovative techniques, is being developed through a Ph.D. research study in the School of Engineering to process extensive piles of data for analysis. In this case, AI has been trained on the existing database of numerous engine tests (dynamometer, onboard diagnostics) and is capable of differentiating between two very similar scenarios or outliers.

6. Benefits and Impact of AI-Driven Quality Control Systems

The proposed AI-driven quality control system is expected to provide immediate and transformative impacts on U.S. manufacturing. The adoption of automated, intelligent, and non-contact quality control will help revitalize U.S. manufacturing and strengthen the competitiveness of U.S. industries. The benefits of such AI-driven quality control systems to U.S. industry could be multifarious, and we highlight four of the many promising impacts in this document. They are (1) improved and new product quality, (2) enhanced accuracy, low latency, and fewer defects, (3) potential investment opportunities, and (4) the revival of U.S. manufacturing. Product quality and inspection standards are central topics for U.S. industry. Automated and robust non-contact quality control systems could revolutionize the manufacturing industry and result in significant societal and economic gains.

AI-driven quality control can reduce costs and has wide-ranging effects on manufacturing, with an impact beyond the company level. Automating the quality control process will significantly increase production efficiency. Additionally, automation allows the continuous monitoring of products and process quality. This near real-time awareness could allow the capabilities of AI-driven systems to have a profound transformation on manufacturing. Manufacturers can better understand and control production, identify discrepancies and improvements in supply chains resulting in fewer bottlenecks or backlogs, and remain future-forward in producing the next most innovative technologies. AI-driven quality control systems provide production enhancement opportunities beyond the indicative inspection results and the purchasing price.

6.1. Improved Product Quality

The adoption of AI-QC technology can help alleviate many of the quality control problems mentioned earlier, as it can track numerous individual welding characteristics and use this information to determine how well multiple sensors and spray guns are working together. Additionally, this type of technology can show how well the program is set up for a specific job; for example, a leg on the chairs is not supposed to break during a pull test. Much like a CT scan, the picture would only show the flaw and not remedy the problem. Most of today's welding manufacturers fear warranty costs and disgruntled customers due to faulty welds. The use of this technology will eliminate any product that was not welded to the specific program.

The improved quality in U.S. manufacturing from the adoption of such AI technologies can also be expressed with improved lists of work opportunities and issues. For example, we can develop "premium" lists of the very best U.S. manufacturing companies by industry, based on such indicators as low percentage of products returned, or small variations in products due to poor quality/raw materials, or other indicators. This idea relates to implementing profitwaves in the manufacturing industry, identified by Cooper and Slagmulder of DeFacto. Such "premium" organizations and their practices would be utilized as our standard of excellence, in the identification of effective practices and their spread in society. Concerning work issues, the percentage of good quality products that are relevant to the program or value is influenced by operator workload, a consistent schedule, the number of breaks, lack of movement, controls for adjustments of the other components, how well the operator can be trained in the manufacturing industry for increased product quality, a homogeneous gripping pattern at the start, lean production techniques, the percentage of bad welding attempts that were adjusted after the first group, and metal distortion of one or more corners of the seatpan. The boost in quality with this technology was necessary since the entrenched cost of a single chair was not enough to pay for the cost of inferior quality wares and an entire new second shift, which was funded in part by the 2 million dollar strategic partnership.

7. Future Trends and Developments in AI-Driven Quality Control

7.1. AI and Data Science Methods: AI will transform every field, including its application in the industrial domain. Over the next few years, due to the improvement of hardware devices, consumer electronics, smart wearables, and Internet of Things (IoT) technologies, the development of AI applications will make remarkable progress in the manufacturing sector. For instance, other AI and data science methods such as machine and deep learning can be used to provide insights into potentially desirable features and properties of the products of interest. These models can be employed as an alternative to, or in combination with, experimental designs to help better assimilate the information provided by smart sensors, and the solution of the inverse problem to guarantee, with desired accuracy, the association between process settings and product response.

7.2. Artificial intelligence methods and data science can be utilized in combination with or independently from the numerical and computational approaches to aid quality control, especially when there is a lack of data. An attractive feature of supplying AI models with laboratory experimental responses is that they are free from uncertainty and certainly correct. As explained earlier, AI prediction uncertainty derives from a number of sources such as the level of noise in the training target signal, the uncertainty relating to whether the AI model has correctly extracted the underlying trend of the data, the quality of the experimental data used, etc. Given this, a successful AI application can, according to Larkin et al., provide a similarity measure between materials and product quality between experimental and real applications and speed up materials development and improve product robustness while saving retrieval and measurement time and costs.