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Artificial Intelligence in Quality Control: Transforming Manufacturing Processes

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Abstract: The integration of Artificial Intelligence (AI) into Quality Control (QC) is transforming manufacturing by enhancing accuracy, efficiency, and productivity. Traditional QC methods, reliant on manual inspection and basic automation, often fall short in addressing the complexities of modern production environments. This paper presents a review on the application of AI, particularly machine learning, deep learning, and reinforcement learning, in manufacturing QC processes. It explores how AI improves defect detection, predictive maintenance, and process optimization while also identifying key benefits such as increased consistency, reduced operational costs, and data-driven decision-making. The review highlights current challenges, including data quality, high implementation costs, integration with legacy systems, and the need for specialized expertise. Additionally, emerging trends such as edge AI, explainable AI, and collaborative robotics are discussed as future directions. The findings underscore AI's pivotal role in reshaping quality assurance and offer insights into how manufacturers can leverage these technologies for sustainable and scalable improvements in production quality.

Keywords: Artificial Intelligence, Quality Control, Manufacturing, Machine Learning, Deep Learning, Defect Detection, Predictive Maintenance, Process Optimization, Smart Manufacturing

Introduction

In a highly competitive manufacturing environment, high product quality is necessary to ensure customer satisfaction, reduction of production costs, and an increase in productivity. However, with the rising production volumes and increasing consumer expectations, manufacturers are subjected to greater pressure to produce consistent quality and simultaneously increase efficiency. The existing conventional ways of Quality Control (QC), like human inspection, statistical methods, and basic automation, are not flexible enough, cannot be easily scaled, and are less flexible (Sundaram and Zeid, 2023). The methods employed with these methods especially have difficulty in meeting the needs of today's increasingly complex manufacturing processes, wherein small defects are missed or quick, high-volume manufacturing requires faster, more precise solutions (Toorajipour *et al*., 2021).

Manual inspection may consume mediocrity and is prone to errors, while automated systems could miss complex or newly emerging quality issues. It is a challenge for manufacturers whose quality standards must be met in response to rising production demands (Divyansh, 2024). The integration of Artificial Intelligence (AI) is a transformative solution to the integration of QC processes. With Machine Learning (ML) and Deep Learning (DL) specifically, AI brings the capability of learning from data continuously; it means real-time defect detection, predictive maintenance, and optimization of the process (Mohd *et al*., 2021), and also quality control of all sorts of data. As in an AI-driven system, not only are accuracy and speed being improved, but scalability also is being added to meet modern production's needs (Sundaram and Zeid, 2023).

Large data from sensors and cameras fed into AI-based QC systems detect patterns that are not apparent to humans. Deep learning models like Convolutional Neural Networks (CNN) perform better in visual inspection and reduce human error in defect classification (Ramesh *et al*., 2025). Other than that, AI predicts equipment failures so you know how long you will go without a planned downtime and, therefore, how to improve Equipment Effectiveness (OEE) (Das *et al*., 2019). Secondly, AI optimizes production parameters to maintain a consistent product quality and minimize waste.

SCIENCE Publications

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As with AI itself, the adoption of AI comes with a myriad of benefits, but there are challenges, like reliance on high-quality data, bridging old and new, and sizable up-front investment (Plathottam *et al*., 2023). Such complex AI systems also require skilled personnel to manage them, and these personnel may be scant in some industries. In this paper, we examine how AI is impacting QC in manufacturing and look at how AI techniques make manufacturing more efficient, more accurate, and more scalable while addressing the challenges and the advantages of adoption. The paper discusses the way AI could change in the future by reviewing current trends and case studies when it comes to reshaping the role of manufacturing QC using AI.

Research Objectives

The main objectives of this systematic literature review are:

- To determine the role of AI technologies in improving QC processes in manufacturing
- To assess the AI techniques used in QC systems within the manufacturing industry
- To analyze pain points and barriers faced when implementing AI in QC
- To examine the benefits and outcomes of AI-driven QC systems

Research Questions

This review addresses the following research questions:

- RQ1: What AI techniques have been implemented in quality control systems in manufacturing
- RQ2: How has AI transformed traditional QC processes in terms of efficiency, accuracy, and cost
- RQ3: What are the key challenges and limitations associated with AI adoption in quality control

Methods

The method employed for this systematic literature review is based on the following steps that will help to ensure a rigorous and transparent process for identifying, selecting, and analyzing relevant research.

Data Sources and Search Strategy

The literature search was conducted in the following databases:

- IEEE Xplore
- Springer Link and MDPI
- Science Direct

For the search strategy, a combination of keywords and phrases was employed in order to include all search terms for AI in quality control usage within manufacturing. The key search terms included:

- Artificial Intelligence in Quality Control
- AI in Manufacturing
- Machine Learning in QC
- AI for defect detection
- AI-based process optimization
- AI-driven quality improvement

The search was conducted on publications from 2010 to 2025, focusing on peer-reviewed journal articles, conference papers, and industry reports.

Inclusion and Exclusion Criteria

Studies were selected based on the following inclusion and exclusion criteria.

Inclusion Criteria

- Empirical studies, case studies, or experimental papers discussing AI techniques used for quality control in manufacturing
- Articles published between 2010 and 2025
- Studies that focused on the application of machine learning, deep learning, or other AI methodologies in QC
- Research from both academic and industrial perspectives

Exclusion Criteria

- Papers not related to manufacturing or quality control processes
- Studies are primarily theoretical without empirical data or real-world application
- Studies that are not published in peer-reviewed journals or reputable conferences
- Papers older than 2010

Data Collection

A total of 50 articles were selected, out of which 28 were excluded as they did not fulfill the inclusion criteria completely and 6 out of them were not discuss the main topic area, and 3 were duplicates. The selected final 13 articles were then classified based on AI techniques, applications, challenges, and benefits. The investigation of common trends and findings was conducted by means of a qualitative synthesis. A depth review of the articles was done, and the findings were subjected to analysis about the research questions with a view of getting comprehensive insights into the role of AI in quality control (Figure 1).

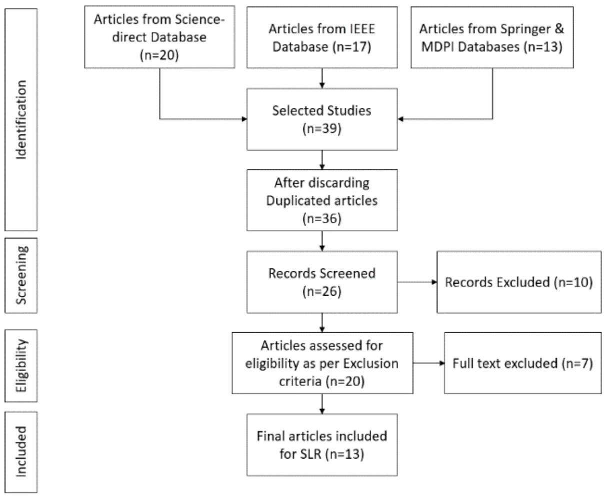

Fig. 1: Flow of systematic literature review for AI in quality control in manufacturing

Data Extraction

A review of each of the selected papers was done based on the key information related to the application of AI in Quality Control (QC). Additionally, it paid attention to what AI techniques were being put into use and included machine learning, deep learning, and reinforcement learning. The applications of AI were also analyzed in defect detection, process optimization, and predictive maintenance, among others. Outcomes were reviewed against accuracy, cost reduction, and efficiency. Then, the last were taken into account: The challenges of the adoption of AI, along with issues and data quality, and skills.

Quality Assessment

Several key criteria were used to assess the quality of each study that was included in this review. After that, the relevance of the study was taken into account to confirm that the study concerned the application of AI in quality control in manufacturing. Excluded were studies that did not concentrate on this specific field. The evaluation of the study's methodological rigor aimed at establishing if the methodology was appropriately described and had been systematically applied. It helped make the findings sound and based on sound research practices. Finally, the contribution to the field was discussed, analyzing specifically if the study made a case for the value of understanding AI in quality control, including its actual existence and results in real life. The review prioritized studies that offered significant practical applications or improvements in the field.

Studies that met the quality criteria were included, while those that lacked sufficient detail or had methodological flaws were excluded from the final analysis.

Critical AI Methods in Quality Control for Manufacturing

The review shows different ways of using Artificial Intelligence (AI) techniques for manufacturing quality control, and it reveals how each of them has advantages according to the particular application. ML, DL, RL, and Fuzzy logic systems are considered by far the most widely used AI techniques in quality control. These methods have necessitated a new way of looking at quality control by enhancing as well as tightening defect detection, process optimization, and predictive maintenance for improved manufacturing efficiency and quality of product.

Anomaly Detection

Anomaly detection can be defined as AI methods meant to detect patterns or data that is expected to behave in a rather different way, or the other way round (see Figure 2). In the manufacturing industry, the technique would be useful in identifying outliers in the production data that may pass unnoticed by traditional methods, which would include unseen product defects or aberrations in the behavior of a machine (Jakubowski *et al.*, 2021). It can also be specifically applicable in the detection of rare, complex, or new-minted defects which have never been encountered.

The anomaly detection algorithms find extensive use in car manufacturing to detect defects in the assembly line: Checking the welding process, misalignment in the car body parts, etc. These artificial Intelligence models analyze the measurements of sensor data on the robotic arms and assembly lines and compare the current measurement patterns to those of the past (Sundaram and Zeid, 2023; Morales *et al.*, 2025). For example, when a welding joint has abnormal temperature changes, which is not normal to the system, it will be treated as an anomaly, and it will prompt the operators. This aids in keeping defects at early stages of production and producing good quality products.

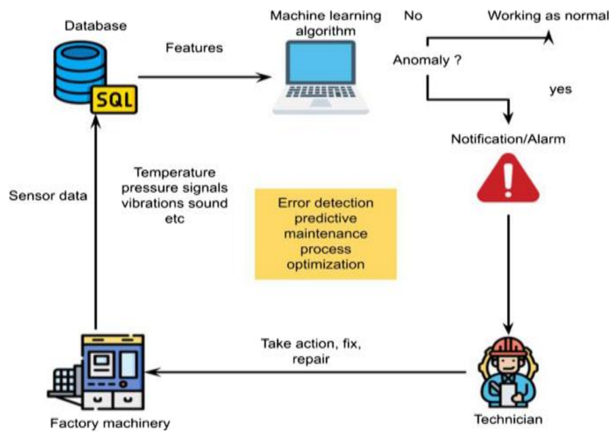

Fig. 2: Anomaly detection in manufacturing in quality control process (Chen *et al.*, 2024)

The performance of each machine is monitored by what is known as anomaly detection in semiconductor fabrication, which tries to detect any deviation of the machine through observing any change of unexpected changes in temperature or pressure. AI models can detect these deviations at an early stage and allow predictive maintenance to be performed before a machine breaks, and in that way, prevent the production of defective chips.

Real-Time Process Monitoring

Monitoring of the real-time processes means constantly tracking the production by AI-based systems. The systems make use of sensor data, cameras, and other surveillance systems that are used to collect real-time data on the quality of products being produced, machine performance, and the overall efficiency of the systems. This style will allow manufacturers to get instant feedback, and this will take less time to identify the problems and address them before the problem expands into bigger problems.

The usage of the AI-powered real-time process monitoring systems during semiconductor production allows monitoring and streamlining the production parameters, including temperature, pressure, and flow rates. As an illustration of this, when a photo lithographical action is carried out, an AI system is used to observe the sensors in order to determine that the exposure procedure is operating within the necessary limits. In case the system senses any difference, the operator is notified instantly so he can take corrective action in real-time and hence avoid mistakes in the manufacturing of chips and increase throughput (Shajari *et al*., 2023).

Real-time monitoring of processes in food manufacturing is applied in order to guarantee product consistency and safety. Phones that use AI read data on sensors in production concerning temperature, humidity, and pressure (see Figure 3). As an example, in a canning factory, AI could be used to make sure that the sealing process is going on under the same pressure so that the flaws could be prevented; this might result in the spoilage of goods (Sonwani *et al*., 2022).

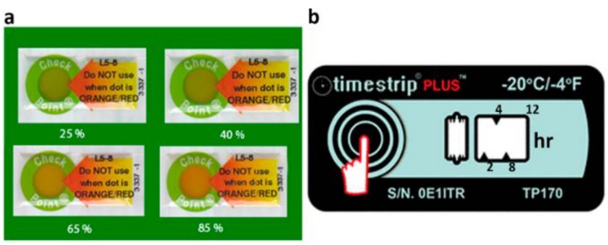

Fig. 3: (a) A sensitive temperature detection system that uses an enzyme-based reaction to signal if a product's integrity has been affected, (b) A crucial time–temperature monitoring system that shows the duration for which the temperature has exceeded a defined limit (Dodero *et al*., 2021)

Automated Testing and Measurements

Automated computerized testing and measurement systems, applying AI techniques, automatically test and measure a product with production line movement. On these systems, it will be possible to issue quality checks with the use of AI models without any human interaction and thus less the possibility of human error and more consistency of measurement. This approach may be used at different points of the manufacturing cycle to check the parameters of the products, their functionality, and other specs (Sarker, 2021).

The AI can also be applied in Printed Circuit Board (PCB) production, where the production line installs AI-based automated testing solutions that check every board to make sure it passes the electrical standard. These tools make use of AI-powered optical inspection tools, which collect voltage and resistance values at multiple positions on the board during assembly. In case a fault has been noticed to occur irregularly, e.g., a broken trace, missing components, misaligned components, among others, then the system signals the operators to rework the board before it actually passes to the next production stage (Chen *et al*., 2023).

Structural test of automotive parts is done through automation. AI-enabled solutions are used to measure the high precision of brake pads to make sure they are safe. There is an automated process to measure the thickness of the pads and check the irregularities in surface qualities that is surely much more efficient and precise than manual testing.

Data-Driven Quality Analytics

Data-driven quality analytics would include AI to process data sets collected in the manufacturing process and extract valuable information that can be used to make a decision. This approach allows a manufacturer to recognize the trends, streamline its procedures, make future projections, and make sound decisions using data. AI models are used to examine past information and real-time information in order to streamline the production line, minimize defects, and enhance the overall process of quality controls.

Textile manufacturers perform quality analytics of fabric defects utilizing AI. AI systems are able to detect minor inconsistencies that may arise through viewing sensor data on weaving machines and visual data coming out of cameras to detect thread tension or color differences. Another example has to do with a machine that always gives slightly varying colors of a fabric made by it. The AI system will evaluate the data pattern and recommend a change to the machine settings. This will result in improved overall fabric and will prevent wastage as the quality will be taken care of early in the process (Ozek *et al*., 2025).

Automation in pharmaceutical manufacturing is achieved through AI-based analytics platforms that

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streamline the manufacture of painkillers and other medicines in the form of tablets. These platforms use information in different steps of production that can include blending, compression, and coating steps in order to determine whether or not the production process is ideal or not. As a case in point, by lying beyond the tolerable limits, the weight of the tablets varies, but keeping up the quality of the product, AI may propose some adjustments to the machine parameters in real-time, thus minimizing wastage of the material.

AI Techniques in Quality Control for Manufacturing

Machine Learning

Several aspects of quality control have been automated using ML techniques (Table 1). For this, specific algorithms, such as Support Vector Machines (SVM), decision trees, and random forests, are used for defect classification, product quality prediction, or anomaly detection in the production process (Ailyn, 2023). Supervised learning, which is a prominent subset of ML, allows the training of models on the labelled dataset, and hence defect classification can happen accurately, and the quality of a product can be predicted using historical data. This comes in particularly handy for domains where the defects are well known and shall be labeled in the training data. Anomaly detection is another subset of ML that is applied in unsupervised learning. Here, the algorithm is trained to recognize deviations from regularity based on it and doesn't require labelled data. The advantage of this method is in discovering new, unexpected defects or unusual abnormalities that were not encountered during the dataset training (Yorulmuş *et al*., 2022).

Deep Learning

Deep Learning (DL) has made great strides in defect detection, especially in complex visual inspection tasks. Convolutional Neural Network (CNN) has widely been used in handling image analysis and surface defect detection in semiconductor chips, printed circuit boards, panels, etc. CNNs learn to extract features from an image and can spot even the minutest surface flaws using high accuracy, thereby decreasing human error in the inspection process. Particularly, Recurrent Neural Networks (RNNs) and more complex Long Short-Term Memory (LSTM) networks are very effective at digesting time series data from the sensor network. Predictive maintenance is an example of the type of work these models are used for, where they look at sensor reads over time to predict when equipment will ultimately fail, in order for maintenance to take place before a final failure that causes major damage or downtime (Hütten *et al*., 2024). Not only does it make uptime better, but it also ensures that production doesn't have unpredictable failures that can result in bad-quality products.

Reinforcement Learning

One of the other key AI techniques for quality control is Reinforcement Learning (RL), which primarily makes use of process optimization. In RL, an agent is an agent learning how to make decisions, interacting with an environment, and receiving feedback on the consequences made by its actions in the form of rewards or penalties. RL algorithms are widely used in manufacturing, where production parameters are adjusted (independently or cooperatively) on the fly (real-time), e.g., to find temperature, speed, or pressure tuning policies to maximize product quality and minimize waste. Thus, this dynamic adjustment makes sure that the production processes maintain their optimality so that the output becomes more consistent and the defects are less (Erharter *et al*., 2021).

Table 1: Key AI Techniques in Quality Control for Manufacturing

AI Technique	Description	Applications	Advantages
Machine Learning (ML)	Utilizes algorithms like SVM, decision trees, and random forests for defect classification, quality prediction, and anomaly detection	Defect classification, product quality prediction, anomaly detection	Automates defect detection and predicts product quality based on historical data
Deep Learning (DL)	Uses CNNs for image analysis and RNNs/LSTMs for time series data to detect defects and predict maintenance needs	Surface defect detection, predictive maintenance for equipment	Reduces human error in visual inspection and predicts equipment failure to avoid production downtime
Reinforcement Learning (RL)	An agent learns optimal production parameters by receiving feedback from its actions to maximize product quality and minimize waste	Process optimization, real-time adjustment of production parameters	Ensures optimal production and reduces defects by adjusting parameters in real time
Fuzzy Logic	Helps decision-making under uncertainty, using imprecise data and mimicking human judgment	Decision-making when data is ambiguous or noisy	Useful in ambiguous data scenarios and simulates human reasoning for consistent QC decisions

Fuzzy Logic

Fuzzy logic, as well as expert systems, are of great importance for decision making in uncertainty. Fuzzy logic is very useful when the data are not precise or the data are ambiguous, and the sensors don't measure exactly. The human reasoning effect adds to reasoning, which mimics human judgment and is possible as a solution where information is vague or imprecise. It can be helpful in cases when QC decisions are made on aspects of the data that are hard to quantify, where the data is noisy. On the other hand, expert systems simulate the steps taken by experienced quality control inspectors to make decisions about the company's product. As with humans, these systems analyze various factors and provide recommendations or decisions using support for cases in which human expertise is necessary but can be mimic seasoned professionals' behavior to keep consistent and accurate quality control standards (Ho *et al*., scarce or unavailable. This means that expert systems can 2010).

These technologies offer a range of benefits, from automating defect detection and predictive maintenance to optimizing production parameters and making decisions under uncertainty

Applications of AI in Manufacturing Quality Control

Artificial Intelligence (AI) has been increasingly integrated into various aspects of manufacturing to enhance Quality Control (QC) processes, transforming the industry by improving efficiency, accuracy, and operational flexibility.

Defect Detection and Inspection

AI has been most effective in defect detection and inspection and is used to assist in making decisions on the same. Hand-held inspections in production lines, especially in electronics and semiconductors industries, whenever there is high-speed production, the methods become unyielding when it comes to small defect identification. AOI is an advanced vision system where a Convolutional Neural Network helps in identifying defects in real-time with a high level of accuracy. But most importantly, CNNs are particularly efficient in analyzing complex images; it is for this reason that these systems can detect defects, which range from surface scratches, chips, as well as other forms of imperfections on the products passing through assembly lines (Hütten *et al*., 2024). First, AI injection facilitates the enhancement of quality control by minimizing the presence of errors during the inspection, increases the rate at which flaws are identified, and makes the whole inspection process more reliable (Kausik *et al*., 2025).

Predictive Maintenance

Yet another essential use case of AI for the manufacturing industry is predictive maintenance, where AI techniques, particularly ML and time series analysis, are used for predicting machine failures in the future. In the conventional production process, an equipment failure is experienced easily, which results in production stoppage. AI, on the other hand, looks at figures, patterns, sensors, vibrations, and several operational parameters over some time in order to determine early signs leading to machinery failure (Pesante-Santana and Woldstad, 2006). It also allows companies to perform maintenance, which will prevent machinery failures in advance and not when it is already too late to avoid equipment downtime. This not only adds efficiency but also makes it possible for there to be steady production throughout and without any halts, which often interfere with the quality of the produced products (Yorulmuş *et al*., 2022).

Process Optimization

Apart from defect detection as well as the use of predictive maintenance, AI is another important factor in the improvement of processes in manufacturing companies. There is also the use of AI in adjusting parameters within production in real-time, resulting from Reinforcement Learning (RL) (Divyansh, 2024). Using the RL algorithms, it is possible to change different parameters such as temperature, pressure, and speed while carrying out production to guarantee that the set parameter gives the best results with minimal wastage. It can also create an optimistic approach for manufacturers to have real-time responses to the fluctuations in production factors, enhance the quality of the produced products, and maximize resources used and minimize wastage. Through the application of AI, one is in a position to be able to attain certain levels of outputs that can be consistent and accurate, and this can be done without having to employ or task another person (Okuyelu and Adaji, 2024).

Real-Time Monitoring

A particular area where artificial intelligence is actually making a lot of difference is in the ability to monitor the production process in real time. Due to IoT devices and AI, it becomes possible to gather real-time data from sensors included in machines and production lines. This information may be real-time, thus enabling the identification of any event that has happened in relation to the quality of the manufacturing process and production efficiency (Rojek *et al*., 2023). Sophisticated AI systems are able to find out deviations from standard or desirable operating conditions and offer advice to the operators, enabling them to address these issues before they cause problems to the quality of the product (Okuyelu and Adaji, 2024). This means that the manufacturing process is being supervised in real-time to enable quality standards to be maintained while adjustments that may take time to be carried out can also be effected promptly.

Supply Chain and Logistics Optimization

Apart from the manufacturing line, it is also being used in supply and operations chain processes to make things more efficient. They use AI in managing inventory, stock, and forecasting the demands of the material to avoid cases where there is no adequate stock for production, leading to extended times of production. AI can be used in demand forecasting and then automatically re-ordering the raw materials and components by recommending to supply them at the right times and in the right quantities as it forecasts that they would be required in the next production runs (Aljohani, 2023). This makes the entire production process less congested, stops any possible hold-up, and increases the opportunities for factories to supply the necessary materials as required by the market. They are also used in planning delivery time and transport of products, which in turn enhances the efficiency of the production timeline (Helo and Hao, 2022).

Benefits of AI in Quality Control

The incorporation of AI in Quality Control (QC) has advantages that make manufacturing processes highly efficient, accurate, and effective. The first benefit is enhanced efficiency and speed of the operations that the businesses undertake. Autonomous tools are applied for assessing objects under analysis, such as automated defect detection and continuous process monitoring, which speeds up the work of the QC. Vision systems, for example, offer the ability to inspect a product without the time-consuming and costly matter of tiring and the ability to recognize and flag any flaw as a product is in the production line, hence greatly improving the throughput rate of a product in the production line (Nweje and Taiwo, 2025). This increase in speed is very helpful in business environments that are highly competitive and require quick turnaround (Hassan *et al*., 2023).

It also enhances accuracy, especially in identifying the areas that contain defects. Convolutional neural networks, which are a subtype of deep learning models, can detect small flaws as compared to inspectors. Algorithms honed on large amounts of data reduce as much as possible the number of false positives and negatives; thereby, faulty items are identified in the production process (Saha *et al*., 2023). This helps to reduce customer returns as well as increase production standards and the quality of the products developed.

There is also a reduction in costs as a benefit of using AI in QC. Through automating the inspections, there will be a drastic reduction in the number of workers needed for the job, and thus, there will be a lesser requirement for wages, also increasing productivity as the process will not require frequent breaks. Additionally, it reduces waste and thus leads to reduced costs of production that ultimately increase profitability (Shivajee *et al*., 2019). In addition, AI accelerates QC processes and stabilizes them by using standard tools, which helps to achieve decreased variability of products and makes every inspection more objective.

Finally, it provides support for decision-making processes, given large amounts of data on production processes in real time (Saha *et al*., 2023). For a manufacturer, the information is valuable inasmuch as it helps in understanding production conditions, likelihood of constraints in production, and allocation of resources, all of which aid in making production better and the final product of higher quality. It also means that AI is capable of recommending changes to the setting of production processes so as to reduce waste and time for production, hence enhancing its efficiency in the manufacturing process.

Challenges and Limitations

There are benefits attached to the usage of AI in the QC of manufacturing processes, but there are several problems associated with its implementation. One of them is weak data quality and data access, as AI models are based on large and high-quality datasets. It is evident that when presented with inaccurate or incomplete data to work on, one can easily be bound to delivering a poor performance and hence be unable to get desirable results. A key challenge is high initial costs, which include costs associated with the implementation of AI machines and systems, upgrading the company's IT infrastructure, as well as personnel training costs, since AI systems can be very expensive and unaffordable for many small manufacturers (Borkowski and Knop, 2016).

There exist other issues, such as compatibility issues with existing software systems. A majority of the manufacturing plants are still using some obsolete tools that are not friendly to AI, which implies that there will be a need to invest in the modernization of the equipment or integrate custom-made solutions. Another limitation is related to scalability, which is an issue since the application of AI solutions in large, complex production environments is technically challenging and requires significant organizational effort (Gholami *et al*., 2017). Last but not least, one of the key challenges for the broad implementation of AI is the scarcity of qualified personnel who can operate AI equipment effectively or can be trained for this purpose, while the manufacturers could readily seek such professionals.

AI offers significant benefits, its successful implementation in QC is hindered by challenges such as data quality, high costs, integration issues, scalability concerns, and a lack of skilled professionals. Overcoming these barriers is crucial for realizing the full potential of AI in manufacturing quality control.

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Discussion

Application of Artificial Intelligence (AI) into manufacturing Quality Control (QC) has proved to be very efficient, accurate, and the process as a whole has been optimized. Due to the growing pressure on the manufacturing industries to provide quality goods and manufacturing costs, this scenario has reduced the relevance of traditional QC methods. The use of manual inspection and simple automation systems causes inefficiency and errors in most cases. AI and specifically the processes of Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) are changing the face of the industry by making real-time defect detection, predictive maintenance, and process optimization available, which conventional systems would not be capable of doing on the same level.

Support Vector Machines (SVM), decision trees, and random forests were some of the most popular machine learning algorithms that helped to automate the defect detection process and predict the quality of a product. By training on huge sets of data, these models offer the capability to recognize defects with high precision and forecast the quality based on the past production information. Moreover, anomaly detection as a valuable subfield of ML has already transformed the manufacturing sector as it has found the previously unnoticed defects or abnormalities, e.g., in assembly lines or the quality of goods that would be left undetected by human operators. This feature is particularly applicable in fast production processes, where slight defects have to be identified.

Such advanced learning algorithms as Convolutional Neural Networks (CNN), and in general, deep learning approaches have demonstrated their exceptional usefulness in visual inspection applications where they have excellent accuracy in detecting the tiniest imperfections in something such as semiconductor chips and printed circuit boards. These models will be able to handle the more complex visual information, lowering human error and increasing the quality measurements. Furthermore, there are methods such as Recurrent Neural Networks (RNNs) and Long Short-term Memory (LSTM) networks, which have displayed good performance in predictive maintenance tasks with time series data of sensor networks to foretell an equipment failure. Since the AI enables manufacturers to carry out maintenance before equipment malfunctions, besides enhancing equipment uptimes, it also leads to more quality goods because production is not hit by unforeseen idle time.

Another strong AI method, dynamic real-time control of manufacturing conditions, this time through parameters like temperature, speed, and pressure, can be done through reinforcement learning. These models communicate with the production environment and learn from the feedback so as to continuously optimize the processes. This real-time optimization also contributes to minimizing wastes and maintaining of steady quality of products in the production line. Using AI-powered reinforcement learning enables a high level of efficiency in manufacturing processes, which lowers the risks of errors and decreases the losses of resources.

With all the benefits, the use of AI in QC has a number of drawbacks. There is one important obstacle, which is the quality of data. AI models need quantity and good quality of data to be able to perform well, and in case of poor or incomplete information, AI systems might not perform well and give the best results. Moreover, financial impediments after turning to AI implementation exist in the form of high initial expenses: Expenses on the hardware, software to be implemented, and staff training are not affordable by many manufacturers, especially small and medium-sized ones. Issue with compatibility with legacy systems is also a concern; older manufacturing equipment may not be able to work with new technologies of AI as well. This will require significant investments to upgrade the infrastructure.

Scalability is yet another issue, given that the implementation of AI solutions on large, intricate industrialized production settings demands not only a high level of technical knowledge but also input in terms of self-organization. Besides, the fact that there is a lack of talent familiar with AI technologies that may skillfully work and control them is also a problem, because many manufacturers cannot find the talent to work with such complex systems using AI.

In the future, the possibilities of AI regarding quality control are colossal. New technologies like edge AI, whereby data can be processed at the local level instead of using cloud stores, are likely to offer quicker decision-making and lower latency. It may result in a more efficient and responsive QC in the manufacturing process. Moreover, the emergence of collaborative robotics, where people will work together with robots with artificial intelligence, has great potential to improve the quality control process by minimizing human errors. Also, explainable AI (XAI) will enhance the transparency and credibility of AI decisions and honesty with manufacturers. The adoption of AI technologies by manufacturers in their QC processes will be possible due to explainable AI.

Although AI offers a wide range of opportunities in terms of quality control in the manufacturing process, it is necessary to address the related issues and achieve the full potential of this technology. Constant innovations in technology will continue to enhance the quality of products produced, increase the efficiency in processes and predictive maintenance, which makes AI a valuable asset in the contemporary manufacturing industry.

Conclusion

In conclusion, AI is revolutionizing the field of QC in manufacturing by providing an opportunity to step up to a new level of breakthrough in the detection of defects, predictions of maintenance, and optimization of processes. In other words, the use of AI in carrying out extensive parts of QC helps in increasing the rate and quality of production at a cheaper price. Besides the time efficiency and better quality of sample check and analysis, AI systems provide manufacturers with opportunities to detect failures, minimize downtimes, and optimize workflows in real time. However, the major disadvantages of implementing CRM systems include issues with data quality, high implementation cost, CRM integration with existing systems, scalability, and a dearth of talent (Escobar *et al*., 2021).

The overall outlook as far as the future of AI in quality control is concerned is promising as follows: New technologies such as edge AI that offer the possibility of performing data processing on localized ends are expected to increase the Quick-Decision making speed, hence increasing the efficiency of QC. The roles of collaborative robotics as people working with human beings have also been projected to be significant in improving other processes and also cutting on human error. Moreover, this idea of explainable AI (XAI) is expected to enhance acceptance in the manufacturing environment for the usage of AI since it aims to increase decision-making transparency (Senoner *et al*., 2022). These trends will only cause further advances in even more complex and flexible QC systems, which would be a great advantage to manufacturers in improving product quality, minimizing waste, and sustaining a competitive edge given the increasing changes in the field of manufacturing industry (Arinez *et al*., 2020).

Even now, the application of AI in quality control is still in the process of development, but its implementation in the manufacturing area is revolutionizing the industry, offering a number of possibilities for improvements and breakthroughs. Mitigating threats and adopting new opportunities will significantly determine how AI enhances the practices of quality control in manufacturing industries.

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Ethics

This study adhered to the ethical standards of research integrity. No human or animal subjects were involved in this research. All data utilized in this work were sourced from publicly available databases, and proper citations have been provided to acknowledge prior research. There are no conflicts of interest to declare.

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