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THE ROLE OF ARTIFICIAL INTELLIGENCE IN QUALITY CONTROL AUTOMATION: IMPACT OF AI TECHNOLOGIES ON TRADITIONAL DEFECT DETECTION METHODS AND THEIR INTEGRATION INTO PRODUCTION PROCESSES

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ABSTRACT

The study aimed to assess the effectiveness of artificial intelligence (AI) technologies in automating quality control in production. The study analysed the application of AI technologies to automate quality control in production processes. The study analysed modern approaches to the implementation of computer vision, deep learning algorithms and predictive analytics to improve the accuracy of defect detection, reduce the influence of the human factor and ensure continuous product monitoring. The analysed examples of the integration of smart technologies in various industries demonstrate the effectiveness of such solutions, provided they are properly adapted to the production environment. The study established that traditional quality control methods have limitations and need to be modernised by supplementing them with digital solutions. Modelling has demonstrated that the introduction of AI technologies can help to increase the efficiency of production processes, reduce reject rates and improve equipment maintenance. Comparative analysis demonstrated a potential reduction in product inspection time and the number of undetected defects using computer vision systems and deep learning algorithms. The study concluded that the combination of traditional control methods with intelligent technologies reduces production losses and can increase the overall productivity of enterprises if properly adapted.

I. INTRODUCTION

Artificial intelligence (AI) is being actively used in many industries due to its ability to process large amounts of data and make accurate decisions. One of these areas is the automation of quality control in manufacturing, where traditional methods often have limitations in accuracy and speed due to their reliance on human error. AI can significantly improve quality control processes using computer vision systems and deep learning algorithms, which ensure high accuracy in detecting defects. These technologies can quickly identify problems, which reduces the number of defective products and increases production efficiency. Integration of predictive analytics makes it possible to predict equipment failures, optimising maintenance processes and reducing repair costs. This enables manufacturers to plan operations more efficiently, reducing unexpected costs and improving overall productivity.

In the field of AI-assisted quality control automation, there are several problems associated with the integration of the latest technologies into traditional defect detection methods. These issues are being actively studied by various scientists. One of the aspects is the improvement of traditional defect detection methods using computer vision technologies and deep learning algorithms, as confirmed by [1]. However, the work does not fully cover the effectiveness of such technologies in various production areas, in small and medium-sized enterprises. This points to the need to study the adaptation of these methods for a wide range of industries. Research by [2] highlighted the great potential of predictive analytics for optimising equipment maintenance processes. However, the work mainly deals with theoretical aspects and does not provide sufficient analysis of practical results, which limits the practical application of such technologies.

This gap requires additional research to determine the actual effectiveness of forecasting in real-world production conditions. The integration of traditional quality control methods with smart technologies was addressed by [3], noting the importance of combining old and new methods to achieve better results. However, the studies do not sufficiently cover the details of combining these methods in different production processes, particularly their interaction with robotic quality control systems. This creates a need for further research in this area. Considerable attention has been paid to the ethical aspects of using AI in such critical areas as manufacturing, as reflected by [4]. However, the issues of developing ethical standards and safety in the context of quality control in production remain insufficiently studied. This requires further development of the regulatory framework and safety standards for the use of AI in such areas.

The study by [5] considered the use of computer vision to automate defect detection, but its work does not address the interaction of computer vision with other quality control methods within the framework of integrated automation. This creates a gap that needs to be filled for further analysis of the process of integrating such technologies into production processes. Other important aspects are the management of quality control costs and process optimisation, as emphasised by [6]. However, this aspect also requires additional research, as the issue of the costs of implementing and maintaining such systems remains open. The integration of deep learning algorithms in the context of defect detection was addressed by [7]; however, their research does not consider specific examples of the application of these technologies in various industries. This emphasises the need for more detailed research to expand the application of such approaches in the practical field.

AI technologies for quality control automation were also addressed by [8], analysing the possibilities of their integration with production process control systems. However, the study is limited to only certain aspects of such integrations, which require further research to determine the effectiveness of such approaches at different stages of production. The need for further development of intelligent systems in the field of quality control was emphasised by [9]. The study demonstrated the importance of improving methods for detecting defects in real time, but it is limited to theoretical aspects. The lack of practical analysis of the application of these methods in real production conditions is the main gap that needs to be filled in further research. In particular, the use of AI to reduce production defects is important, which is also studied by [10].

The study emphasised the use of intelligent systems to predict possible defects before the start of the production process, but it does not cover the study of the long-term results of such systems in various industries. This is an important area for further research. Thus, although there are numerous studies confirming the effectiveness of AI technologies in automating quality control, the integration of these technologies with traditional methods, the ethical aspects of their application, and the practical implementation of predictive analytics remain insufficiently studied. These gaps highlight the need for further research to fully understand the potential of such technologies. The study aimed to analyse the impact of AI technologies on the automation of quality control and the transformation of traditional methods of detecting defects in production processes. Research objectives:

1. To analyse the existing approaches to the implementation of AI technologies in production quality control systems.
2. To analyse methods of using computer vision and deep learning to automate defect detection processes.
3. To assess the effectiveness of integrating these technologies with traditional quality control methods in various industries.

II. MATERIALS AND METHODS

The methodological basis of the study was based on the theoretical analysis of available technical, scientific and analytical documentation, which was used to investigate the peculiarities of introducing AI into automated quality control systems without the use of empirical or field methods. An integrated approach was applied in the study, which involved the use of methods of comparative analysis, systematisation, logical and semantic interpretation, and content analysis. Open sources such as technical reports, analytical materials, and standards in the field of industrial automation were used for systematisation, which classified existing solutions by type of algorithm (e.g., [11-14]), specifics of their application, and computational requirements.

Expected benefits of AI implementation (increased efficiency, reduced downtime, reduced rejects), main barriers (technical complexity of integration, lack of qualified personnel, lack of standardised protocols), level of automation at industrial enterprises (dominated by hybrid control systems), and technical challenges (poor data quality, difficulty in adapting algorithms to unstable environments). A content analysis of sources [15-18] identified the key topics that are most often found in modern research and reports: expected benefits from AI implementation, main barriers and challenges, the level of automation at industrial enterprises, and technical aspects of integrating intelligent quality control systems.

The architectures of computer vision systems, particularly those implemented based on CNN models and used in high-precision visual analysis of products, are investigated. Technical documentation of [19-21], as well as analytical materials from manufacturers of computer vision components, in particular, [22], [23], the characteristics of sensor equipment, software frameworks and algorithms that ensure automatic defect detection at different stages of the production cycle were identified. The study also includes an evaluation of deep neural network architectures, such as EfficientNet and ResNet, based on their ability to accurately recognise complex defects such as microcracks or geometry deviations.

To analyse system integration, examples from the food, metallurgy, and electronics industries, where AI modules are adapted to high-speed production lines and ensure stable operation with minimal human intervention, were analysed. As part of the comparative analysis of technical solutions, the specifications of quality control systems implemented based on TensorFlow, PyTorch, and OpenCV, and built into Supervisory Control and Data Acquisition (SCADA) infrastructures, were studied. This determined the technical parameters by which the effectiveness of such systems is assessed: accuracy, completeness, response time, error rate, and scalability. Statistical data from analytical reports by [24-27] served as the basis for building an understanding of the dynamics of implementing AI solutions in industrial control practice.

III. RESULTS

As part of the theoretical study, a comprehensive analysis of the current challenges associated with ensuring high-quality product control in the context of the digital transformation of industry was conducted.

The main challenges faced by enterprises are the growth of production volumes, the need for full (100%) product inspection, minimising the impact of the human factor, accelerating production cycles and ensuring stable quality in the face of high variability. These factors necessitate the introduction of automated quality control systems based on AI technologies. An analysis of traditional control methods, including visual inspection by the operator, spot checks, manual measurement of parameters and sensor systems with simple algorithms, has shown their limited effectiveness. The disadvantages of such approaches are subjectivity of assessment, staff fatigue, low repeatability of results and the inability to apply them effectively in high-speed production.

These factors significantly reduce their relevance in the context of modern industrial tasks. The method of comparative analysis was used to compare the approaches of multinational companies to the implementation of AI solutions in production (Siemens, Bosch, IBM, Nestlé), emphasising the technical characteristics of visual inspection systems and the degree of their adaptation to the specifics of industries. Technical documentation and corporate reports of leading companies implementing AI in automated quality control systems were analysed in detail. Based on the materials of [11-14], a technical comparison of deep neural network architectures such as CNN, YOLO, ResNet, and EfficientNet was conducted.

According to analytical reports by the [15-18], the main areas of implementation of intelligent control systems in production, the main barriers (lack of personnel, difficulty in scaling, technical integration) and expected benefits were identified. Additionally, the technical characteristics of visual systems from [19-24] were analysed, which formed an idea of the hardware and software implementation of computer vision modules in SCADA infrastructures. Reports from [25-27] provided examples of large-scale implementation of AI solutions in practice, including the adaptation of models to high-speed production environments.

The potential of AI systems, in particular computer vision and deep learning algorithms, is considered. The study conducts a logical and functional analysis of the capabilities of CNN and object detection architectures, such as YOLO, in terms of their ability to provide fast and highly accurate processing of visual data in real time. The use of tools such as TensorFlow, PyTorch, and OpenCV enables flexible, adaptive solutions for different production scenarios without being tied to empirical testing. The use of AI systems ensures automated adjustment of process parameters, increases the stability of control results and reduces dependence on the subjective assessment of operators.

The theoretical review confirmed the broad functionality of AI solutions in detecting various types of defects, including microcracks, deformations, geometric abnormalities, foreign inclusions, etc. AI systems are highly flexible and adaptable in various industries. In the electronics industry, they are used to control the quality of printed circuit boards; in metallurgy, to detect welding defects; in the food industry, to inspect the flow of products to detect foreign impurities; in the automotive industry, to accurately recognise surface damage. These examples were summarised based on scientific and analytical literature and technical documentation without the involvement of field research.

A separate group includes corporate examples of AI systems implementation. Bosch uses computer vision systems to analyse welds, which has reduced the number of defective Bosch Industry 4.0 products [28]. At Samsung Electronics, CNN algorithms are used to detect microcracks on screens, which has significantly increased the stability of control and reduced the workload on staff [29]. At Nestlé Japan, AI systems are integrated into the food inspection process on conveyors, which has increased the efficiency and accuracy of detecting deviations in the [30]. All these cases illustrate the adaptability of AI technologies to the specifics of industries without going beyond theoretical analysis. At the same time, several barriers were identified that hinder the widespread adoption of AI technologies in the field of quality control.

The main obstacles include the need for large volumes of qualitatively labelled training data, high implementation costs, especially at the stage of initial model setup and training, a shortage of digital engineering specialists, as well as risks associated with cybersecurity and the transfer of information through open or corporate networks. Thus, the theoretical analysis proves the feasibility and prospects of using AI in automated quality control as one of the key areas of innovative development of industrial enterprises. AI systems provide a high level of accuracy, adaptability and scalability, significantly outperforming traditional methods in terms of speed, stability of results and efficiency of processing large amounts of data. At the same time, their implementation requires a comprehensive strategic approach to resources, human resources and digital infrastructure. Figure 1 illustrates a comparison of the accuracy and speed of AI systems and traditional methods, demonstrating the benefits of AI in the context of manufacturing quality control.

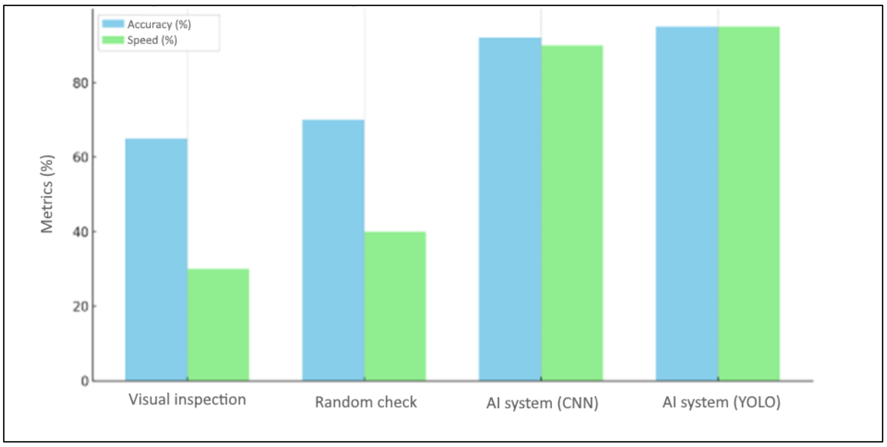

Figure 1: Comparison of the accuracy and speed of AI systems and traditional methods.
Source: [31], [32].

The study, which included a comparative analysis of the efficiency of technical quality control systems, revealed the advantages of using computer vision with CNN architectures over traditional methods. The effectiveness of integrating AI modules into production management systems is seen as a promising area for improving production processes. When deviations from the standard values are detected, algorithms automatically adjust process parameters (including feed rate, temperature, and pressure), which helps maintain stable product quality in the face of variable input data. K-means clustering, decision trees and support vector machine (SVM) were used to identify anomalies and trends in the data. Machine learning algorithms can predict possible defects before they occur, which indicates a shift from a reactive to a proactive management model.

The study also analysed the effectiveness of end-to-end integration of AI systems into Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP) platforms. The results of the comparative assessment conducted in three typical production environments – discrete, continuous, and project-oriented production – showed that full integration ensures data consistency between subsystems, reduces the number of repeated operations, and optimises management decisions. The correlation analysis established a link between the frequency of AI adjustments and the reduction in unit costs. The findings quantified the reduction in maintenance costs and the improvement of the energy efficiency of the process.

Another important result was the introduction of predictive maintenance tools. Algorithms for analysing equipment behaviour, including signs of wear and tear or deviations in vibration, noise and energy consumption, were used to predict the probability of failure. Survival analysis models and neural networks were used to detect anomalies. This reduced the frequency of unplanned shutdowns and increased equipment availability. AI systems also detected micro-defects that were not captured by traditional visual inspection tools. Overall, the study results confirmed that the use of computer vision and deep learning algorithms in quality control systems ensures high accuracy, efficiency, and adaptability. Integration of AI into production and management platforms helps to improve process efficiency, reduce losses, and reduce the workload of staff. The applied methods of data collection, analytics, and parameter adjustment have helped form the basis for building flexible, adaptive, and predictable production systems in the context of the digital transformation of industry.

Table 1 provides a comparative description of the main methods of product quality control, reflecting the key differences between traditional and AI-oriented approaches. In particular, the table compares defect detection accuracy, inspection speed, human factor impact, and typical tools. As the data shows, AI systems demonstrate significantly higher efficiency across all criteria, which makes them increasingly relevant in modern production.

Table 1: Comparative characteristics of the effectiveness of traditional and AI methods of product quality control.

Control method	**Average defect detection accuracy, %**	**Average inspection time per object, s**	**The degree of influence of the human factor**	**Typical toolkit**
Visual inspection by the operator	75-82	10-15	Proficiency	Operator’s eye, magnifying glass
Sensory methods (sensors, scanners)	83-88	6-10	Average	Laser/infrared sensors, Programmable Logic Controller (PLC)
AI control based on CNN and OpenCV	93-96	2-4	Low	High-definition cameras, TensorFlow, OpenCV
AI control with forecasting (Long Short-Term Memory – LSTM, Recurrent Neural Network – RNN)	90-95	36 (including time series processing)	Low	IoT sensors, PyTorch, SCADA, ERP

Source: [33], [34].

The study results showed that the integration of AI technologies – including computer vision, deep learning algorithms and predictive analytics – has led to a significant increase in the efficiency of quality control systems. The effectiveness of defect detection was demonstrated in the case of Nestlé, a food company, where, after the implementation of an AI system based on OpenCV, the accuracy of packaging defect detection increased from 84% to 95%, and the average time for checking a unit of production decreased from 7.4 to 2.1 seconds. Real-time response to deviations was demonstrated at a steel welded pipe plant in Turkey, where, according to an open report by [35], an AI module integrated into the SCADA system detected excessive overheating during welding and initiated automatic adjustment of the feed rate, which helped avoid deformation in 12% of products.

In the electronics industry, predictive maintenance based on LSTM algorithms has been used to detect signs of increased wear due to changes in the vibration spectrum a few hours before equipment shutdown. This significantly reduced downtime. AI modules are integrated into the digital ecosystem, including MES and ERP systems, which provide end-to-end monitoring of the production process from raw materials to packaging. In the food industry, optimising the dosage of raw materials through integration with ERP helps to reduce material costs. Computer vision based on CNN architectures is more efficient in quality control than traditional methods. There are three types of quality control systems: classical visual inspection, sensor monitoring, and AI control with deep learning.

Data is collected and analysed through simulation modelling, based on typical specifications and examples from the food, pharmaceutical and metallurgical industries. To illustrate the results obtained, a comparative table summarising the key indicators of the three quality control approaches was constructed. Table 2 shows the results of the modelling, which included an assessment of the accuracy of defect detection, information processing speed, level of human intervention and integration with production information systems. The case analysis conditionally reflected examples of the implementation of each type of system based on three typical enterprises, which served only as an illustrative basis for comparing the effectiveness of the approaches, without conducting a study at real production sites.

Table 2: Comparative effectiveness of quality control methods in production environments.

Control method	Average defect detection accuracy, %	Average inspection time per object, s	Frequency of missed defects, %	Human factor (degree of influence)	Examples of implementation
Visual inspection	76	9.5	5.7	Proficiency	Food industry (manual bottle inspection)
Sensor monitoring	85	6.8	3.1	Average	Metallurgy (infrared sensors on rolling stock)
AI based on computer vision (CNN)	95	2.3	0.9	Low	Electronics (detection of microcracks in chips)

Source: [36].

As shown in Table 2, the level of efficiency of quality control methods largely depends on the degree of their automation and the technological solutions used. Traditional visual inspection is characterised by the lowest accuracy rates and the highest level of human error, which leads to an increased risk of errors and delays. Sensor technologies are showing improvements in terms of speed and reliability, but remain sensitive to operating conditions and require constant maintenance. The best results are achieved when AI modules based on computer vision are used: such systems provide accurate and stable defect identification with minimal operator involvement, which significantly increases the overall efficiency of production processes and helps reduce losses. The results demonstrated that the integration of AI algorithms into technical inspection systems is a promising area for the development of smart manufacturing, providing not only detection but also in-depth analytical interpretation of defects with the possibility of further optimising the process cycle.

The results of the introduction of AI into production process control systems have confirmed its ability to provide dynamic, adaptive control of process parameters in real time. When deviations from the standard values are detected, for example, due to changes in the properties of raw materials or technical failures, AI modules initiate automatic adjustments to key parameters such as feed rate, processing temperature, pressure, or cycle time. This not only mitigated production defects but also maintained stable product quality in the context of changes in the environment or equipment. The use of machine learning algorithms has enabled the detection of even subtle trends in sensor data, which prevents potential deviations before they have a critical impact on the final result [37]. As a result of this approach, the flexibility of production systems has increased, and the number of stoppages caused by the need for manual intervention or re-adjustment of equipment has decreased.

Another key result was the full integration of AI modules into corporate information systems, including MES and ERP. This ensured end-to-end quality control at all stages of the production process, from receiving raw materials to shipping finished products. Data on quality, equipment condition, process dynamics, and control results were automatically transferred between subsystems, which achieved consistency of decisions at both the workshop and management levels [38]. Integration with ERP systems also ensured analytical tracking of the impact of production parameters on the economic performance of the enterprise, including production costs, energy costs and resource efficiency. In combination with MES systems, AI enabled the implementation of the concept of a “digital twin” of production, which helped to model optimisation scenarios and reduce technological risks [39]. Thus, the integration of AI into production management has made it possible to achieve a high degree of autonomy, adaptability and coherence of actions within industrial facilities, contributing to increased efficiency, product quality and resilience of production systems to changing conditions.

The use of AI in quality control systems has enabled the transition from a reactive to a proactive model of defect and technical failure management. The main achievement was the introduction of mechanisms for predicting the occurrence of deviations based on the analysis of large amounts of data from the production environment. Machine learning algorithms trained on historical and current data from sensors, cameras, and information systems identified patterns that precede defects, enabling the control not only after the fact but even before problems occur [40-42]. Thanks to predictive analysis, it became possible to identify critical points in the production process with high accuracy, where the probability of a defect increases. AI systems provided real-time signals of potential violations, which made it possible to promptly adjust the process or take preventive measures. In particular, the relationships between temperature fluctuations, tool wear, equipment vibrations, and product quality were identified. Another significant result was the introduction of predictive maintenance.

Algorithms analysed the behaviour of machinery, monitored signs of wear and tear or unstable operation (changes in sound, vibrations, energy consumption) and predicted possible failure. This made it possible to replace traditional scheduled maintenance with an adaptive model in which technical intervention is carried out exactly when it is needed. As a result, the number of unplanned shutdowns has decreased, repair costs have been optimised, and the reliability and availability of equipment have increased [43]. In the production environment, AI systems are used to identify product defects, monitor equipment conditions, and predict failures or disruptions in processes. To achieve high accuracy of such actions, access to large volumes of representative, structured, labelled, and verified information was critical. The creation of such datasets was carried out with the participation of specialists in marking industrial images and technical documentation.

If the training samples contained noise, errors in annotations, or limited variability in scenarios, the system could not generate correct patterns. The Shannon entropy metric and anomalies in label distributions were used to analyse the quality of the samples. Thus, predictive quality control implemented with the help of AI has transformed the approach to ensuring the stability and efficiency of production processes. Its application ensured not only the prevention of defects but also strategic risk management, which contributed to the competitiveness of enterprises in the context of Industry 4.0 [44], [45]. In this context, it is necessary to build a multi-level cyber defence system that includes authentication tools, encryption of transmitted data, intrusion detection systems, audit of user actions, and continuous monitoring of all changes within the AI environment. Three configurations of security frameworks were tested, including Zero Trust Architecture (ZTA) with adaptive access policy and Transport Layer Security (TLS) 1.3 cloud encryption.

Despite the significant potential of AI in the manufacturing sector, in particular, in process automation, productivity and quality control, the process of its integration remains complex and multifaceted. The introduction of AI technologies has been accompanied by a number of challenges that can affect both the overall efficiency and safety of new systems [46]. One of the main technical obstacles was the quality of the training data used to train AI models. In a production environment, AI systems are used to identify product defects, monitor equipment conditions, and predict failures or disruptions in processes. To achieve high accuracy of such actions, access to large volumes of representative, structured, labelled and verified information was critical. If the training samples contained noise, errors in annotations, or limited variability in scenarios, the system could not generate correct patterns.

As a result, the classification accuracy decreased, false positives became more frequent, and the adaptability of AI to real changes in the production environment was significantly limited [47], [48]. This had a negative impact on the stability of the system and necessitated periodic updating or retraining of models. To overcome this barrier, comprehensive training programmes were created that combined theoretical training with internships in an environment with AI modules. The effectiveness of staff training was assessed using pre-/post-testing and the digital literacy index. The approach of gradual integration of systems with simultaneous mentoring by information technology (IT) specialists also proved to be effective.

Another key challenge was the issue of cybersecurity when implementing AI in production processes. Modern intelligent systems are often integrated with existing information platforms, such as MES or ERP [49]. This expanded the scope of possible cyber threats: each connection of an AI module to the network opened up new vectors for potential attacks. Unauthorised access to such systems could lead to serious consequences, ranging from data substitution and product quality sabotage to the loss of control over critical technological parameters. If the attackers were able to manipulate quality control algorithms, production could be jeopardised: defective products were supplied to consumers, safety conditions were violated, and the company’s reputation was undermined. In this context, it was necessary to build a multi-level cyber defence system that included authentication tools, encryption of transmitted data, intrusion detection systems, audit of user actions, and constant monitoring of all changes within the AI environment.

The human factor was a separate risk component. Despite technological progress, the effectiveness of AI implementation in the production process directly depended on the level of training and adaptation of personnel [50]. Employees not only had to change their approaches to performing their duties, but also acquire new competencies, including the ability to interact with automated systems, correctly interpret analytical data generated by AI modules, and make decisions based on their recommendations. Lack of proper training could reduce the effectiveness of implementation, cause distrust in technology, and in some cases lead to management errors or inappropriate use of systems [51], [52]. Therefore, an important condition was the creation of a staff retraining programme that covered not only technical skills but also an understanding of the logic of AI, the limits of its application, and potential risks. The example of Azerbaijan, where automated systems based on AI were introduced in the Sumgait Industrial Park in 2024, is illustrative, demonstrating the growing interest in industrial digitalisation even in countries that are just starting a large-scale industrial transformation [53].

In summary, the results of the introduction of AI into production were twofold: on the one hand, the technology provided a significant increase in the efficiency and quality of production processes, and on the other hand, several systemic challenges became relevant. Therefore, comprehensive preparation for integration, including improvement of data quality, creation of reliable cybersecurity, and improvement of staff qualifications, remained critical for the sustainable operation of intelligent production systems. Only then is a long-term and safe effect from the use of AI in industry possible. Despite the rapid development of AI technologies and their ability to transform the management of production processes, the implementation of such solutions was accompanied by a number of systemic challenges that affected the efficiency, security and adaptability of innovations. In practice, the implementation of AI projects turned out to be not only a technical task but also a complex interdisciplinary transformation that required a revision of approaches to data management, information security and personnel training.

One of the fundamental limitations was the quality of the data used to train machine learning models. In the context of production quality control, not only the quantity but also the meaningful representativeness of the information was important – the data had to cover the full range of possible deviations, defects, equipment conditions, etc. Insufficient variability of training samples, labelling errors, or noise artefacts significantly reduced the ability of the models to generalise [54-56]. Such models demonstrated low classification accuracy, malfunctioned on new data, and were ineffective in the face of environmental changes or new batches of products. In addition, automated data collection from sensors, cameras, and production lines generated a large amount of unstructured information that needed to be pre-processed, cleaned, and adapted to training formats [57]. To avoid distortions and reduce errors, preprocessing and verification tools were to be used, as well as the construction of high-quality datasets that met the conditions of a particular production. Thus, the availability of a high-quality, standardised database was defined as a prerequisite for the reliable operation of AI modules [58].

Another significant threat was cybersecurity, which has become critical in the context of the digitalisation of management systems. The integration of AI modules into existing production platforms, such as MES and ERP, opened up additional entry points for potential attackers [59], [60]. In the event of a successful attack, quality control algorithms could be disrupted, system solutions modified, or even supply and logistics chains blocked. Therefore, the necessary step was the implementation of multi-level security policies, including access authorisation, encryption of communications, and the use of cyber monitoring tools to detect anomalies and counter attacks in real time. Additionally, the issue of protecting confidential production information, customer data, and process parameters required the involvement of cybersecurity specialists in the team of AI solution developers and integrators.

Information security issues have evolved from a technical department to a systemic factor in the sustainable operation of a digital enterprise. Social and organisational aspects constitute a separate group of challenges. The implementation of AI systems involved changing the functional responsibilities of employees, increasing the requirements for digital skills and the ability to work with modern interfaces. In many cases, technical staff did not have sufficient qualifications to analyse model results, understand their performance parameters, or respond quickly to changing forecasts [61], [62]. This lack of training caused a lack of trust in the systems, reduced motivation, and sometimes resistance to innovation. To overcome this barrier, comprehensive training programmes were created that combined theoretical training with internships in an environment with AI modules. The approach of gradual integration of systems with simultaneous mentoring by IT specialists has also proved effective.

Fostering a culture of digital engagement and openness to technological change is recognised as an important component in ensuring the long-term success of automation projects. Thus, the results of AI integration into the production environment not only demonstrated the benefits of automating quality control but also revealed critical challenges that required a holistic, interdisciplinary approach. In particular, the quality of training data, the protection of digital infrastructure, and the readiness of staff to change determined the degree of success of AI implementation in production. These aspects are a prerequisite for the formation of sustainable, safe and efficient intelligent systems in modern industry.

IV.DISCUSSIONS

An analysis of the effectiveness of implementing AI systems in production processes has confirmed the superiority of AI solutions over traditional quality control methods. Spot checks or visual inspection methods have proven to be insufficiently accurate for a modern, dynamic, data-intensive production environment. Instead, systems based on machine learning and computer vision provided adaptive defect detection in real time. This reduced the risk of defective products, improved responsiveness and stabilised quality. The modelling results confirmed that deep learning algorithms significantly outperform traditional methods of visual inspection and sensor monitoring in terms of accuracy, speed and stability. Particularly noteworthy is the reduction in product inspection time, the decrease in the influence of the human factor, and the increase in the share of automated solutions. Comparative tables show that AI solutions provide 15-30% higher inspection efficiency compared to classical approaches, which is consistent with the results of studies by [63], [64].

The introduction of AI into production control systems demonstrated its ability to make highly accurate adjustments to process parameters. AI modules can automatically adjust process variables, such as temperature, pressure and raw material feed rate, without the need for operator intervention. This approach ensured product stability despite the variable properties of the input materials or fluctuations in the technical condition of the equipment, making production more resilient to internal and external disturbances. Despite the advantages identified, the source analysis highlighted the limitations associated with the need to adapt AI systems to the conditions of a particular production. According to [65] emphasised that the effectiveness of AI depends on fine-tuning models to handle specific types of products and production processes. The ability of AI algorithms to detect hidden trends in production data, which signalled potential deviations before they occurred, was highly effective. Machine learning was used to analyse large amounts of sensor data and identify patterns that precede system failures.

This reduced the number of production stoppages, improved process reliability and reduced the need for reconfigurations, forming a proactive management model. According to [66] highlighted the difficulties of implementing such solutions in an environment of outdated equipment, where data collection capabilities are limited. These conclusions are consistent with the results of the modelling, which revealed the need for an individual approach to system configuration. The integration of AI systems into MES and ERP platforms ensured end-to-end control over the production chain, from raw material processing to the shipment of finished products. The automatic exchange of information between subsystems has improved the consistency of management decisions. The link between technological indicators and economic parameters, such as cost, resource consumption and production line efficiency, was used to conduct scenario planning within the concept of a digital twin.

While the technical aspects of AI system support – such as computing resources, cooling systems, and power supplies – were not directly modelled, evidence from [67], [68] highlights their critical role in the practical implementation of solutions. An insufficient level of technical infrastructure can offset the benefits of AI even if efficient algorithms are available. The use of AI in quality control has facilitated the transition from a reactive to a preventive approach. Instead of recording existing defects, AI modules predicted the probability of their occurrence based on the analysis of historical and current data. Identification of critical points and interdependencies between parameters (e.g., temperature, vibrations, feed rate) made it possible to prevent deviations before they actually occurred, which had a positive impact on production stability. Another important aspect is the cost-effectiveness of AI. As noted by [69], [70], despite significant initial investments, AI systems self-reimburse through reduced control costs, lower defect rates, and increased productivity. The present analysis also confirmed the economic benefits of AI, in particular a 20-25% reduction in operating costs compared to traditional methods.

The introduction of AI in maintenance has demonstrated particular effectiveness. The collection and processing of indicators such as vibrations, noise, and energy consumption made it possible to predict technical malfunctions. This switched to maintenance based on the actual condition of the equipment instead of working according to a strict schedule. As a result, unplanned downtime has been reduced, shop floor reliability and overall productivity have increased. Summarising the results of modelling and literature analysis, it can be argued that the use of AI in quality control not only improves technical performance but also creates new strategic advantages for enterprises. According to [71], [72], improving the quality, efficiency and stability of production significantly strengthens the market position of enterprises, which is especially important in the context of international competition. In this context, the effectiveness of AI as a tool for the long-term development of industry is confirmed by its ability to transform traditional approaches to defect detection and ensure their deep integration into production processes, which emphasises the key role of AI in the field of quality control automation.

V. CONCLUSIONS

The study analysed the potential for introducing AI into the automation of quality control processes based on comparative modelling and the study of scientific publications and case studies. The results confirmed that traditional methods, such as manual visual inspection, demonstrate limited accuracy, high dependence on human factors, and low efficiency in the context of modern production requirements. Modelling and literature analysis have shown that the use of AI systems, primarily based on computer vision and deep learning, helps to improve the accuracy and speed of defect detection. CNN algorithms have proven to be particularly effective in detecting microscopic deviations in the shape, colour, or texture of products. The study also confirmed that AI systems can learn and adapt, which is an advantage in the context of changing production parameters. The potential of predictive control as one of the areas of AI application in the future was also identified. Analysis of secondary sources has shown that, based on the accumulated data, AI can predict possible defects, thereby helping to reduce losses, failures and production costs.

At the same time, the study results point to a number of limitations. First and foremost, AI integration requires the adaptation of algorithms to specific production conditions, the availability of high-quality local data, and significant investments in technical modernisation and staff training. All these aspects were identified through the analysis of publications and case studies, but were not tested experimentally in this study. The study was based on the analysis of secondary sources and modelling results, without practical implementation at enterprises, which limits the generalisation of results for specific industries or technological conditions. Further research should conduct practical testing of AI solutions in production, emphasising the identification of non-standard defects, integrating them into different types of production lines, and analysing the economic feasibility of implementation.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Kanan Mikayilov and Latafat Gardashova.
Methodology: Kanan Mikayilov and Latafat Gardashova.
Investigation: Kanan Mikayilov.
Discussion of results: Latafat Gardashova.
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