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Application of deep neural networks to automate production quality control in real time

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Abstract. The purpose of the study was to investigate the impact of using deep neural networks on improving the efficiency of automated quality control in contemporary production. The analysis of the application of advanced technologies, such as computer vision, machine learning, and deep neural networks, to automate quality control processes in production conditions was carried out. Successful implementations of automated quality control systems at enterprises such as Bayerische Motoren Werke AG, Siemens, and Nikon were considered as practical examples. The data obtained confirmed that the use of convolutional neural networks for image and video processing, autoencoders, and generative conflicting networks provides high accuracy and speed in detecting defects. In particular, an increase in the accuracy of defect identification was recorded from 80% to 95%, completeness – from 85% to 92%, specificity – from 90% to 98%. The speed of image and video processing increased fivefold – from 5 minutes to 1 minute per unit of production, which significantly reduced the control cycle time. Improving the defect detection rate to 95% helped to reduce the cost of manual verification and minimise the impact of the human factor. The conducted comparative analysis confirmed that automated systems based on deep neural networks significantly outperform conventional methods of monitoring key performance metrics. The study also showed that the integration of such systems with data processing peripherals and cloud platforms provides high flexibility and scalability of production processes. The economic assessment showed a significant reduction in labour costs and the number of errors, and an increase in the overall productivity of enterprises using automated quality control systems. The results obtained can be used as practical recommendations for companies interested in implementing innovative approaches to product quality assurance

Keywords: intelligent monitoring of production quality; data processing speed; machine learning; defect detection; computer vision; autoencoders

Introduction

Advanced manufacturing processes require high precision and efficiency, especially in the field of quality control. Conventional methods of product inspection are often not fast and flexible enough, which can lead to an increase in manufacturing defects and financial losses. The use of deep neural networks to automate real-time quality control opens up new opportunities for improving productivity and optimising production processes. The application of computer vision and deep learning techniques allows to analyse product images with high accuracy, automatically detecting defects and anomalies. The use of convolutional neural networks (CNNs) provides effective recognition of visual defects, autoencoders and generative adversarial networks (GANs) help in detecting subtle deviations, and recurrent neural networks (RNNs) can predict possible defects even before they appear. The relevance of employing such methods is also supported by research in related industrial fields: modern computer vision techniques, particularly machine learning methods, can be successfully used for measurement and reconstruction of objects even in hard-to-reach conditions (Belytskyi *et al*. 2023). This demonstrates the flexibility and adaptability of computer vision and machine learning to complex manufacturing challenges.

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One of the main difficulties is to ensure maximum accuracy and speed of analysis, since the quality control system must work in real time, without creating delays in the production process. In addition, deep learning models must be flexible enough to adapt to different product types, lighting changes, changes in production conditions, and the appearance of new defects. Another problem is the need to process large amounts of data, which requires significant computing power. The quality of neural networks largely depends on the availability of large amounts of annotated data, which can be a problem for businesses that do not have enough samples with real defects.

One of the key problems is the reliability of defect detection, since automated systems can also skip defective products, which reduces the quality of production, and give false positive positives, causing unnecessary costs. However, investigating the effectiveness of deep learning algorithms for analysing the quality of printed products, A.P. Bondarchuk *et al*. (2024) determined that their use can reduce the number of defects. The study by R. Thakur *et al*. (2023) showed high accuracy in detecting defects using neural networks in the textile industry, which significantly exceeds conventional verification methods. Y. Banadaki *et al*. (2021) proposed an automated approach for quality control and manufacturing process in additive manufacturing based on deep CNNs. The researchers showed that the use of CNN models significantly improved the accuracy of defect detection at the initial stages of production and reduced the number of deviations in the final product, which positively affects the overall productivity of the enterprise. In turn, M.R. Islam *et al*. (2024) in their analysis proved the effectiveness of implementing computer vision and deep learning technologies for automating quality control. Processing visual information using these methods allowed timely detection of violations, minimising operator involvement, and ensuring the stability of technological processes.

Growing demands on product quality and the speed of production processes encouraged the search for new approaches to automate quality control. S. Sundaram & A. Zeid (2023) reviewed the use of artificial intelligence (AI) to create intelligent quality control systems in manufacturing processes. As a result of their research, ways were proposed to reduce the burden on personnel by introducing automatic systems for collecting and analysing visual data, using self-learning algorithms to identify defects without human intervention, and integrating visualisation interfaces that simplify monitoring and decision-making. S. Prymyska *et al*. (2025) focused on integrating AI into automated industrial process systems, in particular, improving the efficiency of production management and the accuracy of defect detection using AI. The results of their study highlighted the importance of creating flexible and scalable solutions that can be seamlessly integrated into existing production lines without disrupting their functioning.

One problem is that the high computational demand of neural networks and the need to adapt to changing production conditions can cause real-time delays. To overcome these challenges, M. Shahin *et al*. (2024) focused on using a universal CNN to optimise production processes. In particular, the use of CNN allows reducing the time of product verification, optimise the use of resources, and automate individual production operations without compromising the stability of the technological process. J. Zipfel *et al*. (2023) in their study examined the use of unsupervised deep learning techniques to detect anomalies in industrial processes. They compared different models and concluded that unsupervised learning can effectively detect defects even without large annotated data sets. The results showed that unsupervised methods can be particularly useful in complex production environments where conventional approaches are often ineffective.

All the studies reviewed demonstrated the significant potential of deep neural networks, in particular, for detecting defects in real time, improving accuracy, and reducing the impact of the human factor on product quality. However, there are certain challenges, including high computational requirements, the need to adapt to changing production conditions, and dependence on large amounts of annotated data, which limits their use in some production environments. The purpose of this study was to explore the potential of using deep neural networks to automate the quality control process in production and determine the level of their effectiveness. To achieve the research goal, the following tasks were defined: to review advanced technologies for automating quality control; to investigate the architecture and models of deep neural networks used for quality control; to evaluate the possibilities of using automated quality control systems based on deep neural networks.

Materials and Methods

The study was implemented in several stages using a combination of theoretical, analytical, and experimental methods. At the first stage of the study, a review of advanced technologies for automating quality control, including conventional control methods, was conducted. Special attention was paid to the use of computer vision, machine learning, and deep neural networks in quality control. The method of analysing literature sources and open implementation cases was applied. In particular, the use of computer vision to detect defects in BMW (Bayerische Motoren Werke) production lines (Germany), the use of machine learning to monitor the quality of electronic components (Siemens, Germany), and integration of deep neural networks for lens verification in cameras (Nikon, Japan). The goal of this stage was to identify technologies with the highest potential for use in the production environment and identify their limitations and advantages.

At the second stage, the main architectural approaches to the use of deep neural networks in quality control were analysed. In particular, the use of CNNs, autoencoders, and GANs for anomaly analysis, which helps to find defects without the need for a large amount of training data. Special attention was paid to RNNs, Long Short-Term Memory (LSTM), which were used to predict possible deviations in production processes, which allowed preventing the occurrence of defects even at the early stages of production.

The third stage analysed the sources and structure of data needed to train models, in particular, images, video streams, sensor metrics, and Internet of Things (IoT) data, which are critical for quality control in production processes. Data preparation methods were also investigated, such as the process of annotation and data markup for correct model training, which included manual and automated defect markup. In addition, data augmentation techniques were investigated to improve the generalisation of deep learning models, in particular, changes in brightness, rotation, scaling, and the use of noise filters.

At the next stage of the study, the conceptual architecture of the automated quality control system was developed, the main focus was on the integration of neural networks and the choice of technologies for real-time operation. The architecture includes software for image processing and sensor data, neural network modules for defect analysis, and a communication system between components. The quality control infrastructure was evaluated in terms of using core approaches such as Edge AI (processing data on peripherals) and Cloud AI (using cloud services for more complex computing).

A comparative analysis of the effectiveness of an automated quality control system based on deep neural networks and conventional methods was carried out. A method for quantifying results based on key metrics, such as accuracy, recall, and specificity, was used. A table has been created to compare the main performance indicators, in particular, the level of defect detection, data processing speed, and the economic feasibility of implementing automated solutions.

Results

Overview of advanced quality control methods and practical cases of using neural networks in industry

Conventional quality control methods, such as manual inspections, visual inspection, and measurement using standard tools, have several significant limitations. First of all, these methods often require significant time costs, which can reduce the efficiency of production processes. Since most conventional methods depend on human intervention, it also increases the risk of errors due to the human factor. In addition, conventional methods do not always provide sufficient accuracy, especially in conditions of high quality requirements, such as in the production of microelectronics or aviation equipment. Measuring instruments used in conventional control may be limited in accuracy, especially for complex or small parts. Another important limitation is the need for a large number of qualified personnel, which increases the cost of training and maintaining the necessary measurement equipment. Conventional methods are also not flexible, which makes them insufficiently adapted to rapidly changing production conditions or new technologies. They are often not integrated into automated production systems, which makes it difficult to process control results and interact with other stages of the production process (Lu *et al.*, 2020). Thus, although conventional quality control methods are still used in some areas, they have significant limitations that reduce the efficiency and accuracy of quality control in modern production environments.

The use of computer vision, machine learning and deep neural networks in quality control is one of the most promising trends in contemporary manufacturing (Villalba-Diez *et al.*, 2019). These technologies allow automating verification processes and improving the accuracy and speed of real-time quality control. Computer vision based on image processing allows systems with automatic defect detection to analyse visual data, such as images or videos obtained with cameras. This allows detecting defects on production lines, such as cracks, deformations, or other visual disturbances, much faster and with high accuracy compared to conventional methods. Machine learning, in particular, is used to create models that can adapt to different conditions and improve their accuracy over time based on new data. Based on machine learning algorithms, systems can automatically learn from large amounts of data, increasing their efficiency in the production process. Deep neural networks play a key role in improving the quality control process, as they can analyse more complex patterns in data that cannot always be recognised by conventional methods. They allow automatically classifying defects at different stages of production, which reduces the number of errors and ensures high accuracy in detecting problems at an early stage. Together, these technologies create a powerful tool for real-time quality control, providing significant savings in time and resources, and improving the overall efficiency of production processes.

Successful implementation of quality control automation technologies, in particular, using computer vision, machine learning, and deep neural networks, has become important stages of development in many manufacturing companies. For example, BMW uses computer vision to automatically detect defects in car bodies on assembly lines (Misra & Tiwari, 2022). The system, which is based on deep neural networks, provides high accuracy in detecting even the smallest surface defects, which significantly improves product quality and reduces the cost of manual verification. The operation of the system is organised as follows: at different stages of production, the body passes through specially installed high-precision cameras that scan its surface from different angles under different lighting conditions. The resulting images are transmitted in real time to a computing centre, where a deep neural network processes them and analyses them for damage – scratches, dents, cracks, or other defects. The neural network model has been pretrained on a large set of defect examples, which allows it to recognise even small deviations from the norm. Each detected defect is automatically classified by type and severity. Based on the results of the analysis, the system either confirms the product's compliance with quality standards, or issues a signal about the need for additional verification or elimination of the defect.

Another example is Siemens, which has implemented a machine learning system for product quality control during the production phase of electronic components (Schmitt *et al*., 2020). Machine learning algorithms help to analyse large amounts of data collected at different stages of production to identify potential defects before they hit the market. Siemens uses data acquisition systems from sensors located along the production line: this can include data on temperature, vibration, pressure, electrical parameters, and visual characteristics of products. The collected data is sent to a centralised analytical platform, where it is processed using classification algorithms and predictive analysis. Machine learning allows identifying hidden patterns between changes in parameters at different stages of production and the probability of defects in the final product.

Nikon has also successfully integrated deep neural network technologies for automatic lens verification in its cameras (Dorafshan *et al.*, 2018). A real-time system not only detects defects, but also classifies problematic elements, helping to quickly take measures to eliminate them. Based on these implementations, companies were able to achieve significant discounts on production process costs, improve product quality, and significantly reduce the time required to check for defects. Table 1 shows a comparison of three automated quality control technologies in production.

Table 1. Intelligent quality control technologies in production

Name of technology	Key features	Advantages	Restrictions	Example of practical use	Implementation performance
Computer vision	Detection of defects in images or videos. Detection of damage, deviations, and defects on surfaces (such as car bodies)	High accuracy in detecting defects, the ability to work with large amounts of data in real time, reducing the cost of manual verification	Dependence on image quality and lighting, the need for a significant amount of data to train the model	BMW: automatic detection of defects on car bodies on assembly lines	Reduced manual inspection costs, improved defect detection accuracy, and improved product quality
Machine learning	Data analysis to detect anomalies and defects in manufacturing processes. Bounce prediction based on historical data and statistics	It can handle large amounts of data, automatically detect potential defects based on patterns, predict and prevent failures	Requires a large amount of data for effective training, and is difficult to integrate into real-world production processes without significantly modifying existing systems	Siemens: detection of defects at the stage of production of electronic components using machine learning algorithms	Reduced failure rate, improved production efficiency
Deep neural networks	Detection and classification of defects in real time. Use for complex tasks, such as checking lenses that require high accuracy in each element	High detection accuracy of even minimal defects, classification ability with high efficiency, real-time operation speed	They require significant computational resources, the need for large amounts of training data, and sensitivity to changes in production conditions and the environment	Nikon: real-time lens testing in cameras using deep neural networks	Reduced time to check for defects, improved product quality, reduced production costs

Source: compiled by the author

All three technologies have demonstrated high efficiency in improving the quality of production processes. Computer vision allows automating visual inspection and improving the accuracy of detecting defects on product surfaces. Machine learning works effectively with large amounts of production data, helping to predict and prevent the appearance of defects even at the production stage. Deep neural networks provide particularly high processing accuracy and speed, making them ideal for complex real-time quality control tasks. The introduction of these technologies allowed enterprises not only to increase the competitiveness of their products, but also to significantly optimise costs, reduce inspection time, and minimise the risks of manufacturing defects.

The use of deep neural networks to detect defects in manufacturing processes

Automatic quality control systems are critical to achieving high accuracy and efficiency in production processes. Advanced technologies, in particular, deep neural networks, provide automation for detecting defects and anomalies, analysing data, and predicting deviations. In particular, CNNs can efficiently process images to detect defects in products, autoencoders and GANs are used to detect complex anomalies in data, and RNNs and their improved versions, such as LSTM, specialise in predicting changes in the time series of production processes. Each of these architectures has unique advantages and capabilities, which allows them to be integrated into different stages of the production cycle to improve quality and efficiency.

CNNs are among the most common deep neural network models used for manufacturing defect detection tasks, particularly in quality control automation (Li *et al.*, 2021). CNNs are highly efficient in image processing and analysis, making them ideal for use in defect detection systems on production lines where visual data needs to be analysed quickly and accurately. The CNN architecture is based on several key steps: convolution, sub-discretisation, and full-link layers, allowing networks to automatically highlight image features without having to manually configure filters or characteristics.

In the context of quality control, CNNs are used to detect various defects, such as cracks, scratches, misalignments, or other defects in products. Convolutional layers, which are the main elements of this architecture, perform convolution operations, which allows the model to detect spatial relationships in images, such as textures and patterns. This allows the neural network to effectively identify defects even with minimal changes in their appearance. After that, during the sub-discretisation and filtering stages, the network reduces the dimension of images, while preserving important features, which allows faster and more accurate classification.

The use of CNN in the context of quality control can significantly reduce dependence on the human factor, since automatically detected defects can be classified and analysed in real time. Due to their self-learning ability, such models become more accurate over time as they adapt to new data and various variations in defects. This increases not only the speed of problem detection, but also the overall efficiency of the quality control process. Thus, the use of CNN in a real production environment allows for significant improvements in accuracy and performance, reducing the cost of manual control and reducing the likelihood of defects in the final stages of production.

Autoencoders and GANs are powerful tools for analysing anomalies in quality control systems (Ghojogh *et al.*, 2021). Both of these deep neural network architectures can effectively detect deviations from normal patterns, which allows detecting defects on production lines with high accuracy. Their use is especially appropriate in cases where the volume of samples with defects is limited or the data is incomplete.

Autoencoders are neural networks that learn to reproduce their inputs at the output, while simultaneously compressing information in internal latent space (Mienye & Swart, 2025). This allows autoencoders to study normal data patterns and then compare the new input data with the reconstructed outputs. If the input image or other data is very different from what the network has learned as normal, the autoencoder outputs a large reconstruction error rate, which is a signal of the presence of an anomaly. In the context of quality control, autoencoders are used to detect defects in products, such as scratches, cracks, or other manufacturing defects that do not meet quality standards. These models are particularly useful in situations where there are no clear markers for defects and anomalies must be detected due to differences in common data patterns.

GANs consist of two parts: a generator and a discriminator (Fig. 1). The generator creates new data samples that are similar to the real ones, and the discriminator tries to distinguish them from the real ones. In the context of anomaly detection, GANs can be used to train the generator to create “normal” data samples, and the discriminator is trained to recognise differences between true and generated samples. When new data differs significantly from normal samples, the discriminator can indicate anomalies because the generator will not be able to reproduce them correctly. GANs work well for detecting complex anomalies that can be difficult to detect using conventional methods or autoencoders. In particular, they can analyse high-complexity data, such as images, and detect even minor anomalies that may indicate defects in production.

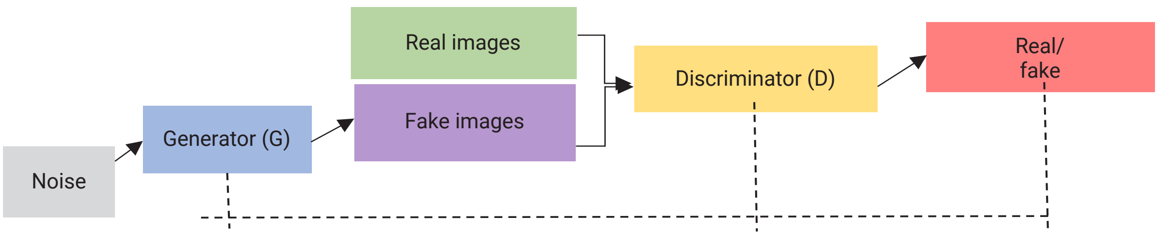

Figure 1. Basic architecture of GAN

Source: compiled by the author based on D.O. Borovyk (2024)

RNNs and their advanced variants, such as LSTM, are powerful tools for predicting possible deviations in production processes. A distinctive feature of these networks is their ability to store information about previous states in a series of data, which allows considering time dependencies that are crucial for analysing and predicting the behaviour of production processes. RNNs work well with consistent data, where it is important to consider the context of previous observations. In the case of real-time quality control, RNNs can analyse data from production lines, such as temperature, speed, or other parameters, to identify trends or anomalies that may indicate potential deviations from the norm. For example, networks can detect signals that indicate possible problems in processes, such as changes in specifications or mechanical problems, before these deviations become critical.

LSTM, as an improved version of RNN, is a more efficient tool for forecasting in complex and long-term time series. Due to their architecture, LSTMs can store important information for a long period of time, which allows them to better work with data that has long-term dependencies. In the context of manufacturing processes, LSTM can predict potential deviations in real time based on historical data, in particular, by predicting changes in product quality or the need for equipment maintenance. This allows for preventive intervention and prevents defects from occurring before they become a serious problem.

For a better understanding of the various deep neural network architectures and their applications in automated quality control, comparative Table 2 is presented below. It demonstrates the key features of each architecture, its advantages and optimal areas of use within the framework of quality control on production lines. This allows summarising the results of the analysis and makes it easier to choose the appropriate model for specific production conditions.

Table 2. Deep neural network architectures for automated quality control

Architecture	Description	Advantages	Restrictions	Application in quality control
CNN	Image processing networks that use convolution layers to highlight features	High efficiency in processing visual data, automatic selection of important features without manual configuration	Training requires a lot of data, and it is difficult to process complex images with minimal defects	Detection of visual defects (cracks, scratches, misalignment) on products
Autoencoders	Networks that learn to reproduce input data at the output by compressing information in latent space	They detect anomalies well and work effectively without well-defined defect markers	They may be less accurate for complex defects or minor anomalies	Detection of anomalies and defects that do not have clear markers (for example, minimal deviations in quality)
GAN	Networks consisting of a generator and discriminator for creating new patterns and detecting anomalies	Powerful for detecting complex, unusual anomalies, capable of working with high-dimensional data	It can be difficult to set up and train, and requires significant resources	Detection of complex anomalies in images, even those that have minor differences from normal ones
RNN	Networks that store information about previous states are suitable for working with time series of data	Great for predicting and analysing time dependencies, and preserving the context of past data	They may be less effective when working with off-the-shelf data, and require large amounts of data for training	Predicting changes in production processes, identifying trends or anomalies in time series
LSTM	The RNN extension, which allows storing information for a long period of time, works well with long-term dependencies	They are better able to cope with long-term time addictions and can learn over long time series	It can be more computationally expensive and requires more resources	Forecasting long-term deviations in processes, equipment maintenance, predicting defects based on historical data

Source: compiled by the author

All architectures have unique advantages for automated quality control. CNN is the best choice for processing visual data, such as detecting defects on the surface of products. Autoencoders are well suited for detecting anomalies where defects may not be obvious or there are no clear signs. GANs are very powerful in the context of detecting complex anomalies, such as minor defects that are difficult to detect even with the human eye. RNNs and their improved version, LSTMs, are powerful tools for analysing time dependencies and predicting changes in production processes. In general, the use of these models in a real production environment can significantly improve the efficiency of quality control, reducing the likelihood of defects, improving accuracy, and reducing the cost of manual control.

Data collection, preparation and augmentation for training deep learning models in automated quality control

Data collection and preparation are the basis for successful training of deep learning models, in particular, in the tasks of automating quality control in production. It is important to choose the right data sources, collect them, and pre-process them to create an effective database for training models. A variety of data sources are used for automated quality control: images, video streams, sensor metrics, and IoT devices. Images and video streams provide visual information about the state of production processes, which allows detecting defects or anomalies. Sensors measure physical parameters such as temperature or pressure, which is also important for evaluating product quality. IoT devices integrate data from various sources and allow monitoring processes in real time.

Annotation and markup of data are important stages in preparing data for training. These include accurate identification of objects or anomalies in images and videos, which helps neural networks to classify new data. For sensor data, it is important to define thresholds that allow detecting anomalies in indicators. Accurate annotation is the basis for further training of models and correct identification of defects. Data augmentation can improve the learning quality of neural networks by artificially increasing the amount of training data (Hernández-García & König, 2018). This is done by changing image parameters such as rotation, zooming, changing lighting, or adding noise. Augmentation makes models more resistant to input variability and improves their accuracy, even with a limited amount of original data. In addition, augmentation allows the model to be more adaptive to different conditions and input variability, which is crucial for real-world production processes where various deviations can occur. This not only improves the accuracy of detecting defects or anomalies, but also reduces the risk of retraining models on a limited data set. In addition to augmentation, careful selection of characteristics, adjustment of hyperparameters, and the use of regularisation methods are also important to ensure the stability and efficiency of models in real-world production control conditions. For effective training of deep learning models, it is important to organise the data preparation process systematically. Table 3 shows the main stages of this process and their characteristics.

Table 3. Key stages of data preparation for training deep learning models

Data preparation stage	Description	Examples of methods/techniques	Application in quality control automation
Data collection	Process of collecting data from various sources (images, videos, sensors, IoT)	Visual data (images, videos), sensors (temperature, pressure), IoT data	Detection of defects on products, monitoring of physical parameters
Data preprocessing	Clearing data and preparing it for training	Normalisation, noise filtering, elimination of missing values	Improving data quality for correct model training
Annotation and markup of data	Identification of objects or anomalies in images or videos	Identification of defects, classification of objects	Preparation of data for training defect detection models
Data augmentation	Increase of the amount of data through transformations	Rotate, zoom, change lighting, add noise	Improvement of the stability of models to data variability
Selecting attributes	Identification of important features for model training	Use of filters for image processing, highlighting the characteristics of touch data	Improvement of model accuracy and reduction of its complexity
Data separation	Division of data into training, validation, and test sets	Statistical distribution of data	Evaluation of the accuracy and ability of the model to generalise

Source: compiled by the author based on N.R. Njeri (2022)

Data preparation is an integral part of the successful implementation of deep learning systems in production. Each step – from collection and preprocessing to annotation and augmentation – helps to improve the accuracy of models, their resistance to data variations, and their ability to detect defects in a timely manner. Proper organisation of the data preparation process provides the basis for building reliable automated quality control systems.

Integration of Edge AI and Cloud AI into automated quality control systems in production

The implementation of an automated quality control system in production requires the creation of an efficient and flexible architecture that allows monitoring and detecting defects in real time. The architecture of such a system includes several main components: data collection and processing, training and execution of models, and interfaces for interacting with other elements of the production line. The system usually includes sensors, cameras, video cameras, and IoT devices that collect data in real time. This data is transmitted to central servers or processing devices, where preprocessing, annotation, and subsequent analysis are performed.

Integration of neural networks into such a system is a critical stage, since they are the ones that automatically detect defects, classify products, and evaluate quality based on the collected data. To achieve high efficiency of such systems, it is important to choose an architecture that supports data processing on both on-site devices (Edge AI) and in the Cloud (Cloud AI). Edge AI assumes that data processing and model execution are performed directly on devices such as cameras or sensors, which reduces latency and increases the system's response rate (Singh & Gill, 2023). This is important when instant analysis and decision-making is required, such as when a defect is detected on a production line. This allows instantly stopping or adjusting the process, ensuring continuous high product quality.

On the other hand, Cloud AI allows processing large amounts of data coming from multiple sensors and cameras and perform more complex analytical operations (Ramamoorthi, 2023). The cloud infrastructure allows using more powerful computing resources to train models on large data sets that can include a variety of production scenarios and conditions. Cloud services also allow integrating and centrally managing data from different sources, providing unified control over production processes. Edge AI and Cloud AI complement each other in quality control systems. For a better understanding of the features of using Edge AI and Cloud AI in production automated quality control systems, Table 4 shows a comparison of both infrastructures by key characteristics.

Table 4. Comparative characteristics of data processing in Edge AI and Cloud AI systems

Characteristics	Edge AI	Cloud AI
Purpose	Instant on-site analysis and response	Deep analysis, centralised data storage and processing
Task type	Real-time defect detection, production process monitoring	Model training, big data analytics, long-term analysis
Delay	Very low	Higher via data transfer to the cloud
Computing power	Limited	High (due to powerful server resources)

Table 4. Continued

Characteristics	Edge AI	Cloud AI
Need for the Internet	Minimal or absent	High (permanent connection required)
Example	Real-time detection of cracks on the production line	Training a model for predicting defects based on historical data

Source: compiled by the author based on R. Singh & S.S. Gill (2023), V. Ramamoorthi (2023)

Edge AI provides fast response without delays, which is crucial for instant detection of defects in production, while Cloud AI provides the ability to deeply analyse and train models on large amounts of data. The combined use of both approaches allows developing the most efficient, adaptive, and reliable quality control systems. Combining Edge AI and Cloud AI creates a flexible and scalable system. For simple, fast tasks (for example, checking individual product units), processing can be performed directly on-site, while for more complex analytical tasks or for training models, cloud capabilities are used. Below is a diagram illustrating the sequence of operation of the quality control system using a combined approach of Edge AI and Cloud AI on the example of a production line (Fig. 2).

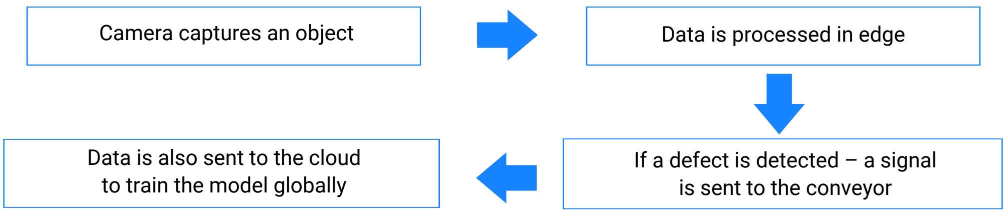

Figure 2. Scheme of operation of a combined quality control system based on Edge AI and Cloud AI
Source: compiled by the author based on R. Singh & S.S. Gill (2023), V. Ramamoorthi (2023)

The operation of such a system can be demonstrated by the example of the production of plastic bottles, where cameras with built-in Edge AI modules are installed on the conveyor, which record each bottle immediately after moulding. Using a pre-trained model on the edge device, instant image analysis is performed: detection of cracks, deformations, under-filling, or contamination. If a defect is detected, the system sends a signal to control the line, and the defective product is automatically rejected. In parallel, all captured images are sent to the cloud server along with the analysis results. It stores the history of quality control, and re-trains the model, considering new defects that were not previously included in the training data. If new types of defects are detected, the updated model is uploaded back to edge devices, improving local accuracy and adaptability of the system. This approach ensures optimal data processing speed and defect detection accuracy, while reducing network load and reducing the need to transmit large amounts of data. Thus, the integration of Edge AI and Cloud AI allows providing operational quality control, but also gradually improving the model based on the accumulated data, forming an adaptive and self-learning system.

Evaluating the effectiveness of an automated quality control system based on deep neural networks in comparison with conventional methods

To evaluate the effectiveness of implementing an automated quality control system using deep neural networks, it is necessary to compare it with traditional methods, evaluating key aspects such as accuracy, speed, expenses, and cost-effectiveness. An important element is also the identification of appropriate key performance indicators that allow evaluating the results achieved. An automated quality control system should ensure high accuracy in detecting defects, fast data processing, and be cost-effective compared to conventional methods, which often require significant time and resources. Performance evaluation can be performed using metrics such as accuracy, completeness, and specificity, which allow objectively comparing results. Below is Table 5 to compare the performance indicators of an automated quality control system and conventional methods.

Table 5. Comparison of the effectiveness of conventional quality control methods and an automated system based on deep neural networks

Indicator	Conventional methods	Automated system (deep neural networks)
Accuracy	80%	95%
Recall	85%	92%
Specificity	90%	98%
Data processing speed	5 minutes per unit of production	1 minute per unit of production
Defect detection rate	80%	95%
Economic efficiency	High labour costs	Reduced labour costs, fewer errors

Source: compiled by the author based on Q. Roy *et al.* (2019)

According to the data presented in Table 5, the automated quality control system based on deep neural networks demonstrates significant advantages compared to traditional methods. Firstly, the accuracy of the automated system is 15% higher than that of conventional approaches, indicating its ability to identify defects much more precisely and with fewer classification errors. The automated system also shows a higher capability in detecting actual defects (92% versus 85%), which reduces the likelihood of defective items being overlooked. Furthermore, the specificity of the AI-based system reaches 98%, indicating a minimisation of false positives – the system is less likely to classify faultless units as defective. Another important indicator is data processing speed, where the automated system proves to be five times more efficient than traditional methods. This significantly accelerates the quality control process, particularly in large-scale production environments. Finally, the defect detection rate also increased by 15% in the neural system, indicating improved reliability of the final product.

From an economic standpoint, automating the quality control process reduces labour costs, since the system requires less human involvement and eliminates errors that often occur due to the human factor. This allows not only to increase efficiency, but also reduce overall production costs. The use of metrics such as accuracy, completeness, and specificity allows clearly assessing the advantages of an automated system over conventional methods. High performance in these metrics indicates that the system is capable of achieving a high level of defect detection, which is crucial for maintaining product quality at a high level.

Discussion

The results of the study showed that quality control automation technologies, in particular, computer vision and deep neural networks, open up new opportunities for manufacturing enterprises, significantly improving the accuracy and speed of defect detection. Compared to conventional methods, which are often based on manual checks or simple measuring tools, automated technologies have many advantages. They not only reduce human error, but also reduce the need for time and resources to perform inspections, which are significant limitations of conventional methods.

Conventional quality control has significant limitations, including high labour intensity and an increased risk of errors due to the human factor. These methods often do not provide the required accuracy, especially in high-tech industries such as automotive or microelectronics. As a result, companies that use only conventional methods may face problems of low efficiency and high costs. This creates an advantage for those who implement automated and technologically advanced approaches. Computer vision, machine learning, and deep neural networks allow automating defect detection at more complex stages of production, ensuring high accuracy even in cases of small or complex defects. Through machine learning, systems can improve their efficiency over time and adapt to changes in production environments.

S. Singh & K. Desai (2023) came to a similar conclusion in their study, noting that the use of computer vision and CNN can significantly improve the process of detecting defects on the surface of materials. The researchers emphasised that the automated system based on these technologies is capable of processing large amounts of visual data in real time, which ensures high accuracy in detecting even the smallest defects, such as cracks, scratches, or irregularities that may not be noticed in traditional quality control. E. Cumbajin *et al*. (2023) also confirmed that the application of machine learning and deep learning technologies to detect defects on the surface of ceramic products can significantly reduce the level of defects, reduce the cost of manual control, and improve overall production efficiency. The researchers proved that automated systems based on computer vision are an important step forward in quality control, as they can work continuously, minimising the human factor and reducing the time required to detect defects.

CNN is a powerful tool for automatically detecting defects in manufacturing processes. Due to its self-learning ability, CNNs can adapt to different variations of defects, which reduces the likelihood of errors that can occur due to the human factor. It also increases the efficiency of the quality control process, reduces the time required for inspection, and reduces the cost of manual control. Autoencoders, on the other hand, are particularly effective when defects do not have clear markers and are detected due to differences in common data patterns. They can learn from normal samples and compare new input images with reconstructed outputs. This approach allows detecting defects such as scratches or cracks, even if they are not obvious. Since autoencoders do not require well-defined signs of defects, they work effectively in situations where it is necessary to detect deviations from normal conditions. In the same area, a study was conducted by H. Chouhad *et al*. (2021), who developed a method for detecting defects on the surface of products using smart data and machine learning technologies for quality control in production processes. I. Ahmed *et al*. (2023) developed a system for detecting anomalies in industrial machines based on the use of autoencoders and deep learning to analyse the characteristics of machines. Both studies focused on automating quality control and defect detection, and focused more on the use of deep neural networks and specific techniques that vary depending on the type of data being processed.

One of the main advantages of RNNs is their ability to store information about previous data states, which is crucial for tasks related to time dependency analysis. In production processes, this allows identifying trends and anomalies that may indicate potential problems at an early stage, which allows taking timely preventive measures to avoid serious defects. Integration of LSTMs into the prediction system provides even greater efficiency, as these networks can handle long-term dependencies in the data. In the case of complex production processes, where information about previous states can have a big impact on future results, LSTMs provide the ability not only to track short-term changes, but also to predict long-term trends. This is important for real-time automated quality control, as it ensures accurate forecasts based on historical data and allows identifying potential defects or maintenance problems in advance. However, for effective training of deep learning models in quality control automation tasks, it is necessary to pay attention to the importance of data collection and preparation. Using a variety of data sources – from images and video streams to sensor metrics and IoT devices – allows creating a comprehensive picture of production processes and effectively monitoring them in real time. Images and videos can help detecting visual defects, while sensors and IoT devices can capture physical parameters that are critical to product quality.

I. Ahmed *et al*. (2023) developed a system for detecting anomalies in industrial machines based on the use of auto-encoders and deep learning. Y. Wang *et al*. (2022) in their paper focused on using RNNs to detect anomalies in time series of data from a production system. Both studies confirmed the importance of processing data from different sources (machines, sensors, time series), which is consistent with current conclusions about the feasibility of integrating technologies for accurate monitoring and automated quality control in real time.

Integration of Edge AI and Cloud AI into an automated quality control system in production is key to improving the efficiency of defect detection. The use of neural networks allows automatically detecting defects and classifying products based on the collected data. The use of edge AI provides instant data processing directly on site, which allows quickly responding to defects and stopping the production process. This is important for simple tasks that require a quick response. On the other hand, Cloud AI allows processing large amounts of data and performing more complex analytical operations. This allows scaling the system and performing deeper analysis from a large number of sources. The combination of these technologies creates a flexible and scalable system that optimises processing time and reduces network load. Simple analysis can be performed on-site, while more complex tasks can be performed in the cloud. This approach provides high speed and accuracy, reducing the need to transfer large amounts of data. However, there are also some problems, such as the stability of the connection between devices and the cloud, which can affect data processing delays. In addition, increasing the number of sensors may require more resources to support the infrastructure.

Similar conclusions were reached by C. Rosca *et al*. (2025), focused on implementing the Artificial Intelligence of Things infrastructure for quality control in the foundry. The researchers examined how the combination of AI and IoT can optimise product monitoring and evaluation processes, providing automatic defect detection and improving the adaptability of production systems. The study focused more on Edge AI and its integration with IoT, suggesting that the study authors view on-premises data processing as a key factor in efficiency, while the role of cloud technologies in these works is less detailed.

Conclusions

The study found that conventional quality control methods, such as manual checks, visual controls, and measurements using standard tools, have significant drawbacks, including low accuracy, high labour intensity, the possibility of human error, and limited flexibility. These methods are not always able to provide the proper level of quality, especially in conditions of complex production processes that require high accuracy. The use of computer vision, machine learning, and deep neural networks is a promising way to improve quality control systems. These technologies allow automating inspection processes and improving the accuracy and speed of defect detection in real time, which significantly increases the efficiency of production processes.

The study focused on the use of CNNs to detect defects on production lines. CNNs efficiently process images, reducing the likelihood of defects in the final stages of production and improving the accuracy and productivity of quality control. Autoencoders are effectively trained to detect anomalies due to differences in patterns, and GANs allow analysing complex defects that are difficult to detect using conventional methods. In addition, the RNN and LSTM architectures have proven their feasibility in predicting and monitoring changes in time series, which is crucial for preventing defects in the early stages of production. The choice of architecture depends on the specifics of production, but their implementation generally helps to improve control accuracy, reduce errors, and optimise costs.

The use of RNNs allows anticipating changes in processes even before they become critical, which increases the effectiveness of quality control. Data collection and preparation are crucial for successful training of deep learning models. The use of various sources (images, sensors, IoT devices) ensures accuracy in detecting defects and anomalies. Data augmentation allows improving the quality of models even with a limited set, making them more resilient and adaptive to changes in the environment. Careful implementation of all stages – from preprocessing to marking, feature selection, and separation – reduces the risk of retraining and ensures stable operation of models in production environments. Thus, a systematic approach to data preparation is a crucial factor in the successful implementation of AI solutions in the field of quality control.

Integration of neural networks into an automated quality control system allows real-time monitoring and detection of defects. Choosing an architecture that combines data processing on devices (Edge AI) and in the cloud (Cloud AI) ensures optimal speed and accuracy. A comparison of Edge AI and Cloud AI systems demonstrated their complementary role in ensuring effective quality control. Edge AI is ideally suited for tasks that require low latency and on-site processing, which is critical for real-time production. The automated quality control system based on deep neural networks showed higher efficiency compared to conventional methods: accuracy increased from 80% to 95%, completeness – from 85% to 92%, specificity – from 90% to 98%. The inspection time of one product unit was reduced from 5 to 1 minute, and the defect detection rate increased from 80% to 95%. Labour costs and the number of errors also decreased, which indicates an overall improvement in the quality and economic feasibility of implementing such a system.

Further research on this topic may include improvements in neural network architectures, including research on new models such as transformers that can better handle large amounts of data and long-time dependencies. Integration of deep neural networks with other technologies, such as IoT and blockchain, will also be an important area to ensure a higher level of automation, data security, and transparency of production processes.

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Conflict of Interest
None.

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Застосування глибоких нейромереж для автоматизації контролю якості виробництва в реальному часі

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Анотація. Метою роботи було дослідити вплив використання глибоких нейронних мереж на підвищення ефективності автоматизованого контролю якості в умовах сучасного виробництва. Було проведено аналіз застосування сучасних технологій, таких як комп'ютерне зір, машинне навчання та глибокі нейронні мережі. В якості практичних прикладів були розглянуті успішні впровадження автоматизованих систем контролю якості на підприємствах, таких як «Bayerische Motoren Werke AG», «Siemens» та «Nikon». Отримані дані підтвердили, що застосування згорткових нейронних мереж для обробки зображень і відео, автоенкодерів та генеративних суперечливих мереж забезпечує високу точність і швидкодію виявлення дефектів. Зокрема, було зафіксовано підвищення точності ідентифікації дефектів з 80 % до 95 %, повноти – з 85 % до 92 %, специфічності – з 90 % до 98 %. Швидкість обробки зображень та відео зросла в п’ять разів – з 5 хвилин до 1 хвилини на одиницю продукції, що дозволило суттєво зменшити час циклу контролю. Удосконалення рівня виявлення дефектів до 95 % сприяло зниженню витрат на ручну перевірку та мінімізації впливу людського фактора. Проведений порівняльний аналіз підтвердив, що автоматизовані системи на основі глибоких нейронних мереж суттєво перевершують традиційні методи контролю за ключовими метриками ефективності. Дослідження також засвідчило, що інтеграція таких систем з периферійними пристроями обробки даних та хмарними платформами забезпечує високу гнучкість і масштабованість виробничих процесів. Економічна оцінка показала значне зниження трудових витрат і кількості помилок, а також зростання загальної продуктивності підприємств при використанні автоматизованих систем контролю якості. Отримані результати можуть бути використані як практичні рекомендації для компаній, зацікавлених у впровадженні інноваційних підходів до забезпечення якості продукції

Ключові слова: інтелектуальний моніторинг виробничої якості; швидкість обробки даних; машинне навчання; виявлення дефектів; комп'ютерний зір; автоенкодери