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# Artificial Intelligence in Industrial Production: A Survey of Concepts, Technologies & Practical Application in an Intelligent Production Environment

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## ABSTRACT

The increasing digitalization of industrial production systems in the context of Industry 4.0 is leading to a growing use of data-driven and intelligent technologies in manufacturing and assembly environments. In particular, Artificial Intelligence (AI), machine learning, and deep learning methods based on neural networks open up new possibilities for the automation of complex decision-making and inspection processes. One of the central application areas in this context is AI-based image processing for visual inspection and quality control. This paper provides a structured and comprehensive overview of the fundamental concepts, technologies, and methods of Artificial Intelligence in the context of industrial production. Among other aspects, relevant neural network architectures with a focus on industrial image processing, typical training and optimization procedures, data preprocessing, and key challenges are addressed. In addition, common application areas of AI in Smart Factory environments are systematically presented. Finally, the paper presents current research at Hochschule Bochum, in which the practical implementation of these technologies using developed neural networks for automated visual quality control in a gearbox assembly process is demonstrated. Lastly, a comparative approach between the AI-based image processing solution and a conventional rule-based machine vision system is presented.

**Keywords:** Artificial intelligence, Smart manufacturing, Deep learning, Machine learning, Automation, Machine vision, Object detection, Object classification

## INTRODUCTION

In recent years, artificial intelligence technologies have experienced a significant upswing. This development has been greatly facilitated by advances in computing power, particularly in the field of graphics processors, as well as by the increasing availability of large and heterogeneous data sets. These technical prerequisites enable the use of powerful machine learning methods and deep neural networks in an ever-increasing number

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of application areas (Lundborg et al., 2023). Since around 2022, there has been a significant increase in public awareness and use of AI technologies. In particular, the widespread availability of powerful AI-based applications, such as generative language and image models (e.g., ChatGPT, Midjourney, or DALL·E), marks a turning point in the public discourse on artificial intelligence (Lundborg et al., 2023; McKinsey, 2022). As a result, AI has increasingly moved beyond purely industrial and scientific environments into the everyday lives of the general population. This development has not only changed the understanding and acceptance of AI systems but also significantly increased expectations regarding their performance and applicability. As a result, the potential for using AI in industrial contexts is also continuing to grow. At the same time, the ongoing digitalization of industrial production systems within the framework of Industry 4.0 is leading to fundamental transformations in manufacturing and assembly processes. Intelligent production concepts enable the comprehensive networking of machines, products, sensor technology, robotics, people, and information systems. By using cyber-physical systems, the Internet of Things (IoT), and real-time communication along the entire value chain, data-driven and intelligent technologies are increasingly becoming the focus of modern production systems (Brabänder, 2025). In this context, artificial intelligence plays a key role as a technology, as it has the potential to automate complex decision-making, analysis, and testing processes that can only be implemented to a limited extent using traditional approaches. Studies show that the number of companies worldwide using AI technologies has roughly doubled since 2017 and has remained consistently high in recent years. The use of AI aims, among other things, to make production and logistics processes more efficient, reduce employees' workload, and improve product quality. Relevant areas of application include manufacturing, logistics, quality control, marketing, and sales. AI-supported image processing systems and machine learning methods are enabling new possibilities in object recognition, object inspection, predictive maintenance, visual quality control, and data-based process monitoring (Pintz et al., 2025). Typical industrial applications include the prediction of process characteristics in real-time operation for inline quality control and the continuous monitoring of production processes and their state variables (Lundborg et al., 2023). With their ability to analyze large amounts of image and sensor data, recognize patterns, and make predictions, AI systems can make production processes more efficient, robust, and flexible. The goal of modern production systems is to achieve high output with minimal waste in the shortest possible time, thereby maximizing overall equipment effectiveness (OEE). Although many production processes are already highly optimized using ERP and MES systems, AI-based approaches offer the potential to include additional relevant process parameters in the analysis and to tap into previously unusable correlations (Netzer et al., 2020). At the same time, the use of AI in industrial applications also presents challenges. These include the availability of high-quality and sufficiently annotated training data, robustness against variable production conditions, integration into existing systems and IT structures, and a lack of qualified personnel and domain-specific AI expertise. In addition, limited financial resources and data security and privacy requirements complicate the implementation of AI systems (Lundborg et al., 2023; Pintz et al., 2025). This paper aims to provide a structured overview of the basic concepts, methods, and fields of application of artificial intelligence in industrial production systems. First, the fundamental principles of AI and relevant methods and training procedures are presented. Subsequently, industrial application areas and key challenges and limitations in implementation are discussed. Building on this general overview, specific research at Bochum University of Applied Sciences is presented, demonstrating the practical implementation of AI applications for automated visual quality control within a realistic smart factory environment.

## STATE OF THE ART: FUNDAMENTAL CONCEPTS AND METHODS OF ARTIFICIAL INTELLIGENCE

Artificial intelligence is a branch of computer science that deals with the development of methods and systems capable of replicating aspects of human thinking, learning, and behavior with the aid of computers. The goal of AI is to automate intelligent behavior by using algorithms that model human-like cognitive abilities such as perception, learning, reasoning, and decision-making (Lundborg et al., 2023). On this basis, machines should be enabled to independently analyze problems, make decisions, and generate solutions for specific use cases. A generally accepted definition describes artificial intelligence as a collective term for a variety of methods that attempt to technically replicate human intelligence. This enables computer systems to perceive and interpret facts, for example, by recognizing objects in image data. In addition, AI systems can learn from feedback and experience, continuously improving their ability to recognize patterns and model complex relationships. The term artificial intelligence is defined differently in scientific literature. John McCarthy describes AI as the science and technology of creating intelligent machines, especially intelligent computer programs (Weber, 2020). Marvin Minsky defines artificial intelligence as the science of making machines perform tasks that, if performed by humans, would require human intelligence (Minsky, 1968). Despite these definitions, artificial intelligence is not equivalent to human intelligence. AI systems are based on algorithms and mathematical models developed by humans, whose results are based on data from the real world. It is therefore a data-driven approach in which computer systems learn from sample data instead of being explicitly programmed for each task. In the industrial environment, AI methods are predominantly used in the context of machine learning (ML). Supervised learning methods, in which models are trained using large, annotated data sets, are particularly widespread. The aim is to learn patterns and correlations from the examples provided to be able to make predictions or decisions for new, unknown data on this basis. Deep learning approaches are particularly used for industrial image processing applications, with convolutional neural networks (CNNs) playing a central role (Frommknecht et al., 2022; Liedtke et al., 1989). These network architectures are specifically designed for processing image data and have proven to be particularly powerful in areas such as image classification, object recognition, and visual inspection (Lundborg et al., 2023). This section, therefore, presents key machine learning methods and architectures that are used in industrial contexts. It explains different approaches and techniques that serve as the basis for AI-based systems in smart factories and production environments.

## LEARNING PARADIGMS IN MACHINE LEARNING

### Machine Learning (ML)

Machine learning is a subfield of artificial intelligence in which models are trained based on available data to recognize patterns and derive predictions or decisions from them. Using such training data sets, AI systems learn to derive correlations and then make predictions or decisions independently, without explicit human programming. This means that the algorithm creates a pattern from data that has already been collected, which the AI can then apply to other data and thereby improve itself. In this way, the AI can optimize and adapt its algorithm based on empirical values (Baker, 2023). Depending on the extent to which humans are involved in the learning process, the algorithms can be supervised or unsupervised to predict results at the end. Assumptions made by humans involved in the creation process of data sets and models for machine learning can lead to AI bias. These biases arise from faulty data and/or its processing and can, for example, lead to or reinforce discrimination against certain groups of people or minorities (Czihlarz, 2020). To simplify the explanation of machine learning, an analogy can be drawn to IF-ELSE logic commonly used in information technology. For example, the AI program should be able to recognize images showing a face from many images. Thus, the algorithm must be able to recognize IF: eyes, nose, mouth, THEN = face. If the recognition is incorrect, the error must be manually identified and corrected by a human. The AI will learn from this correction so that such errors do not occur again. Machine learning is used today, for example, in object recognition and classification for robots and autonomous vehicles. Data in the form of text, images, sensor data, or company key figures can be used for this purpose (Ertel, 2024; Liedtke et al., 1989; Frommknecht et al., 2022).

### Supervised Learning

In supervised learning, models are trained using labeled (annotated) data sets. Each input is assigned a known target output, such as class labels or continuous target values. The goal of training is to learn a mapping between input and output data that can also be generalized to unknown data. Supervised learning is the dominant training method in industrial image processing, especially for tasks such as image classification, object detection, and quality control. Typical algorithms are artificial neural networks, in particular, convolutional neural networks (CNNs). A key challenge is the availability of high-quality and representative training data, as well as the manual effort required for annotation (Frommknecht et al., 2022; Liedtke et al., 1989).

## Unsupervised Learning

In contrast, unsupervised learning does not specify target values. The model analyzes only the structure of the input data and independently identifies patterns, correlations, or groupings. A key method of unsupervised learning is clustering, in which similar data points are grouped together. Well-known algorithms include k-means, hierarchical clustering, and DBSCAN. In industrial applications, unsupervised learning is used for anomaly detection, condition monitoring, and exploratory data analysis, for example, to identify unknown error patterns (Frommknecht et al., 2022; Liedtke et al., 1989).

## Reinforcement Learning (RL)

Reinforcement learning is a paradigm of machine learning in which an agent learns a strategy (policy) for action through interaction with its environment to maximize long-term cumulative reward. In contrast to supervised learning methods, the agent does not receive explicit targets but learns based on rewards and punishments that iteratively influence its behavior. The goal is the gradual optimization of decision-making behavior based on experience-based feedback. The underlying learning methods are based on natural learning processes and can be divided into model-based and model-free approaches. In practice, model-free methods dominate, which can be further divided into value-based and strategy-based methods.

Value-based reinforcement learning methods aim to estimate the expected utility of a state or action in each state. Well-known representatives of this class are Monte Carlo methods and temporal difference learning methods. The agent has a utility or value function that indicates how advantageous a state or action is in terms of the expected reward. For small state and action spaces, this value function can be represented in tabular form, with the entries being updated iteratively based on the rewards received. In complex or high-dimensional state spaces, however, a tabular representation is not practical, so the value function must be approximated. Linear approximation methods, Fourier series, or neural networks, among others, are used for this purpose. A key feature of temporal difference learning is that the value function is adjusted after each action based on the expected future reward, rather than only after the completion of a complete episode. Monte Carlo methods, on the other hand, are based on random simulations and estimate the expected value of the reward based on complete episodes. These methods are often more efficient than deterministic algorithms, but they deliver approximate results with a non-trivial probability. Repeated execution with independent random numbers can reduce the probability of error (Ertel, 2024).

Strategy-based reinforcement learning methods take a different approach by directly parameterizing and optimizing the policy. The goal is to immediately maximize the expected cumulative reward without explicitly estimating a value function. Optimization is typically performed using stochastic gradient-based methods, known as policy gradient methods. These approaches are particularly suitable for continuous state and action spaces and are often used in combination with deep neural networks (Ertel, 2024).

Reinforcement learning is used in robotics, autonomous navigation of vehicles and drones, and process optimization, among other areas. Classic navigation approaches are based in part on metaheuristic methods such as genetic algorithms or swarm intelligence, but these are only suitable for resource-limited systems to a limited extent due to their high computational requirements and complexity. Conventional neural networks can also be used for simple navigation tasks, but their modeling capacity is limited. Deep reinforcement learning combines reinforcement learning with deep neural networks and enables learning in high-dimensional and dynamic environments. In contrast to supervised deep learning approaches, there is no need for the time-consuming creation of large, annotated data sets, as learning takes place via an exploratory trial-and-error approach with continuous feedback. The goal is to develop adaptive systems that can adapt their behavior to real, uncertain environments based on experience (Hawkins, 2019).

## MODEL CLASSES AND AI METHODS

**Neural networks** are a specific type of model in machine learning that is inspired by the structure and functioning of the human brain. They consist of artificial neurons, which represent the nodes in the network and are arranged in different layers. The layers of the neural network are divided into input, output, and hidden layers. The flow of information takes place through the connections between the neurons, with these connections having different weights. The processing and transmission of information takes place in the form of numerical values determined by activation functions and weights. Both the number of connections and their weights play a decisive role. With a higher number of nodes and connections in a neural network, the output value increases due to the different weights (Frommknecht et al., 2022).

### Deep Learning (DL)

Deep learning is an advanced branch of machine learning based on deep artificial neural networks. These networks can process large and complex amounts of data and automatically learn hierarchical feature representations. In contrast to classic machine learning approaches, manual feature extraction is largely eliminated, which is particularly advantageous when processing unstructured data such as images or sensor data. Artificial neural networks consist of an input layer, several hidden layers, and an output layer. Information is processed layer by layer via weighted connections and nonlinear activation functions. The model parameters are adjusted during training using optimization methods such as gradient descent and backpropagation, allowing the network to learn from sample data. Their ability to extract features independently makes deep learning methods particularly suitable for demanding industrial image processing tasks such as object classification, object detection, and visual quality control. Despite the increased demand for training data and computing power, they represent a key technology for intelligent and adaptive production systems (Nguyen et al., 2022; Hawkins et al., 2019; Osinga, 2019).

## SYSTEM ARCHITECTURES AND TRAINING ENVIRONMENTS

### Edge AI

Artificial intelligence enables technical systems to learn from data and apply learned patterns to new situations. Traditionally, computationally intensive AI algorithms are processed in central cloud infrastructures (cloud AI), as this is where the necessary computing power and storage capacity are available. However, with the increasing prevalence of networked and time-critical applications, this approach is reaching its technical and organizational limits. Edge AI describes an approach in which AI functionalities are transferred directly to end devices or decentralized edge systems. Data processing takes place close to the sensors and systems, so that raw data must no longer be continuously transferred to the cloud. Instead, only evaluated information or metadata is passed on. Edge AI systems combine sensors, specialized processors, and AI models to perform analysis and decision-making processes locally. A key advantage of edge AI is the reduction of latency and increased response speed, which is particularly important for safety-critical and time-sensitive applications. In addition, local data processing reduces bandwidth requirements, increases reliability in the event of unstable network connections, and improves data protection, as sensitive raw data does not leave the system. The elimination of a permanent cloud connection also reduces energy consumption. Edge AI is a powerful addition or alternative to cloud-based AI solutions, especially in industrial applications, mobile systems, or environments with limited network infrastructure. It enables robust, energy-efficient, and real-time AI applications and is therefore considered a key component of future intelligent production and assistance systems (Ackeren; 2020, Jänsch, 2019).

### Virtual Environments and Configuration Spaces

To reduce training effort and avoid disrupting real production processes, AI models are increasingly being trained in virtual or simulation environments. These digital environments allow different configuration spaces to be systematically explored, such as variations in process parameters, geometries, or environmental conditions. Especially when combined with reinforcement learning, virtual training environments enable the safe, scalable, and cost-efficient development of AI systems. However, transferring the learned models to real systems requires careful validation to minimize so-called sim-to-real effects (Ertel, 2024).

## DATA-BASED ASPECTS AND TRAINING CHALLENGES

### Training Data and Data Preparation

The quality and significance of an AI model depend largely on the underlying training data. Especially in data-driven processes such as machine learning and deep learning, suitable data sets are a key prerequisite for robust, generalizable models. In industrial applications, training data must be representative of real process conditions and reflect different variants, tolerances, and disruptive influences (Ertel, 2024).

### Data Preprocessing

Structured data preprocessing is required before the actual training. This includes, among other things, cleaning up incorrect or incomplete data sets, normalizing or scaling data, and standardizing formats and resolutions. In image processing, steps such as cropping, color space transformations, and noise reduction are also part of preprocessing. The goal is to increase data quality and avoid systematic distortions that could negatively impact training (Ertel, 2024).

### Annotation and Labeling

In supervised learning, precise annotation of training data is essential. Labeling involves assigning target information to the input data, such as class labels for image classification or bounding boxes for object detection. The manual annotation effort poses a major challenge, especially in industrial scenarios, as expert knowledge is required and incorrect labels can significantly impair model performance. The consistency and quality of the annotation are therefore crucial for the reliability of the trained model (Ertel, 2024).

### Artificial Data Generation and Data Augmentation

To reduce the need for extensive training data, artificial data generation methods are often used. These include data augmentation, in which existing data is expanded through transformations such as rotation, scaling, mirroring, or brightness variation. In addition, synthetic data can be generated using simulations or generative models, especially in virtual environments. These approaches make it possible to specifically map rare or critical scenarios and improve the generalization ability of the model (Ertel, 2024).

### Overfitting and Underfitting

A key goal in training AI models is to strike a balance between model complexity and generalization ability. Overfitting occurs when a model adapts too closely to the training data and learns irrelevant details or noise, resulting in poor performance on unknown data. Underfitting, on the other hand, describes the case where a model is too simple to adequately capture the underlying patterns in the data. Both effects can be reduced by choosing a suitable model, regularization, sufficiently large and diverse datasets, and a clean separation of training, validation, and test data (Ertel, 2024).

## CHALLENGES AND ADVANTAGES OF AI IN COMPANIES

Although the first successful applications of artificial intelligence in industrial practice already exist today, many companies remain cautious about widespread implementation. A key problem is that today's AI solutions are often developed as isolated, stand-alone solutions for individual machines or specific processes. Due to heterogeneous production facilities, there are hardly any standardized models that can be used across processes and states. The transferability and scalability of AI applications to the entire production process is therefore one of the biggest challenges. Technical approaches to solving this problem include the standardization of information models for different machines, the identification of relevant parameters (crawling), and the segmentation of data to create structured databases (clustering). AI approaches can only be scaled efficiently based on such uniform, context-based databases. In addition to technical challenges, however, companies also face organizational and economic hurdles. Studies show that in Germany, unclear cost-benefit ratios, a lack of skilled workers and technical expertise, legal uncertainties, and concerns about IT security are particularly inhibiting implementation. Companies do not have enough qualified personnel to plan, implement, and operate AI projects. At the same time, the necessary financial resources are often lacking, for example for powerful computer infrastructures or training data, especially under the current economic conditions with increased interest rates and changed investment priorities (Büchel et al., 2024). These obstacles contrast with the many opportunities offered by using AI. Intelligent systems can make processes more efficient, reduce waste and material consumption, increase energy efficiency, and enable condition monitoring and predictive maintenance. In addition, AI-supported applications can reduce personnel costs, optimize logistics and distribution, and improve customer service. At the strategic level, AI is a key factor in ensuring competitiveness, as it enables real-time responses to market changes, small-batch production without setup costs, and higher machine utilization. Overall, the introduction of AI in companies is not only a technological challenge, but also an organizational and economic one. Successful implementation, therefore, depends on the availability of high-quality data and technical infrastructure, as well as on expertise, clear business models, and sufficient financial resources (Pintz et al., 2025; Netzer et al., 2020).

## RESEARCH OF THE BOCHUM UNIVERSITY OF APPLIED SCIENCE

The Teaching System for Intelligent Automation (LIA) is a smart factory laboratory environment that serves to investigate, develop, and demonstrate modern Industry 4.0 technologies. The facility aims to simulate realistic industrial production processes and make them accessible for both research purposes and practice-oriented training. As a research and demonstration platform, LIA combines both industry-oriented, market-ready automation solutions and experimental prototypes. This makes the facility particularly suitable for investigating new approaches in the field of intelligent automation, AI-supported production processes, and smart factory concepts. LIA enables innovative technologies to be tested and evaluated under realistic production conditions and gradually integrated into existing industrial structures (Mohr, 2025). As part of the research in the Smart Factory Laboratory Environment (LIA), two AI-based use cases in the field of industrial image processing are being investigated. The aim is to evaluate the potential of neural networks for automated quality control and robot-assisted assembly preparation in a realistic manner. The focus is on the practical implementation, integration, and validation of AI processes under industrial conditions. The first use case involves object classification for checking the assembly status and quality control of gearboxes. The aim is to automatically check the assembly status of the manufactured assemblies and reliably identify potential errors, such as missing or incorrectly assembled components. The second use case addresses object detection for the identification and precise positioning of individual gearbox components. The position and orientation information determined serves as the basis for the automated handling and assembly of the components by a collaborative robot. The Siemens S7-1500 TM-NPU 2.0 is used as the central processing unit. It is equipped with an integrated neural processing unit (NPU) and enables near real-time execution of neural networks directly at the automation level (Siemens, 2025). Image acquisition is performed by a GigE Vision camera (Basler acA1300-60gc), which is connected directly to the controller via Ethernet and serves as the input system for AI processing. The neural networks are developed offline and trained using pre-classified and labeled image datasets. The models are then converted and made available via the Siemens AI Deployer before being integrated into the PLC environment and executed via the TM-NPU. As part of image classification, an AI-based quality inspection system is implemented to monitor the assembly status of the manufactured gearboxes. Before final screw connection, a check is made to ensure that all necessary components are present, and after assembly, a check is made to ensure that the cover has been correctly attached and all screws have been properly inserted. In addition, object detection is implemented to identify and determine the position of individual gearbox components, such as gears and bolts. This application is a key prerequisite for automated assembly, as the components must be separated, recognized, and transferred to a collaborative robot in the correct position after the storage or feeding process. Detection takes place in a defined recognition zone, which is realized by a vibrating table with an integrated lighting table developed in the laboratory, and simulates realistic industrial feeding conditions. The detection model determines the positions of the components and makes this data available for robot-assisted further processing. The combination of classification and detection tasks results in a continuous AI-based image processing process that covers both quality inspection and assembly support. The integrated approach allows a holistic view of the possible applications of neural networks in the smart factory and creates the basis for further investigations, such as the prospective coupling with edge cloud systems to provide process, position, and status data from the intelligent manufacturing plant. This data is used both to build a digital twin and to perform further analyses at the edge level. The goal is data-driven optimization of processes in terms of efficiency, reliability, and quality assurance. Finally, a systematic comparison between AI-based image processing methods and classic rule-based approaches will be carried out. The limitations and strengths of the respective methods, as well as possible dependencies, will be examined. In addition, hybrid approaches will be considered, combining rule-based preprocessing steps with AI models to enable robust and industry-ready complete solutions.

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