

Research on the Application of Artificial Intelligence and Computer Vision Technologies in Industrial Manufacturing

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Abstract: With the deep advancement of Industry 4.0 and smart manufacturing strategies, the traditional industrial manufacturing model is gradually transforming toward digitalization, intellectualization, and refinement. As a core perception technology for smart manufacturing, artificial intelligence computer vision technology features high-precision recognition, high-efficiency computation, and all-weather operation. It breaks through the technical constraints of traditional manual inspection and mechanical monitoring, and becomes a vital driving force for the upgrading of industrial manufacturing. Centering on artificial intelligence computer vision technology, this paper elaborates on its functions in the field of industrial manufacturing. Starting from technical links including data acquisition and preprocessing, feature extraction and pattern recognition, real-time monitoring and feedback control, targeted application strategies are put forward to solve current problems in industrial manufacturing such as low inspection precision, lagging production monitoring, and insufficient automation, and promote in-depth integration between computer vision technology and industrial production.

Keywords: Artificial intelligence; Computer vision; Industrial manufacturing

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1. Introduction

Industrial manufacturing covers diverse scenarios, including component processing, product assembly, quality inspection, equipment operation and maintenance, safety production, and other links, which impose extremely high requirements on perception technologies in terms of precision, real-time performance, and stability. Compared with traditional inspection and monitoring technologies, artificial intelligence computer vision technology abandons the manual-dominated inspection and monitoring modes, and conducts intelligent judgment in a data-driven manner. It can adapt to high-speed production lines, complex working environments, and high-precision detection scenarios, effectively making up for the deficiencies of

traditional manufacturing modes. At present, this technology has been widely applied in numerous industrial sectors such as automobile manufacturing, electronic processing, aerospace, and machinery manufacturing. Nevertheless, practical application still suffers from problems including uneven data quality, low recognition accuracy for complex working condition features, weak support for real-time feedback, and insufficient technical integration. Therefore, this paper analyzes the application value of artificial intelligence computer vision technology in industrial manufacturing and proposes corresponding improvement measures from a technical perspective to raise the automation and intellectualization level of industrial manufacturing.

2. Application value of artificial intelligence computer vision technology in industrial manufacturing

First, it improves production efficiency to realize highly efficient automated production. In traditional industrial production, material sorting, product alignment, component assembly, and finished product classification mostly rely on manual labor. Restricted by human physiological limits, manual work is plagued by slow operation speed, fatigue susceptibility, and unstable efficiency, failing to meet the demands of high-speed modern assembly lines. Artificial intelligence computer vision technology enables uninterrupted automated operation around the clock. By virtue of real-time image recognition and positioning technology, it completes material sorting, workpiece alignment, and product classification at a faster speed than manual labor, fully matching the rhythm of automated assembly lines and drastically shortening production hours ^[1].

Second, it strictly controls product quality to achieve standardized inspection with high precision. Product quality inspection is a core link in industrial manufacturing, directly related to product yield and enterprises' market competitiveness ^[2]. Traditional quality inspection relies on manual visual examination, which depends on operators' experience and concentration. It is prone to missed or false detection of tiny scratches, dimensional deviations, internal blemishes, and assembly defects. In addition, unified standards cannot be guaranteed in manual inspection, failing to satisfy standardized management requirements ^[3]. Equipped with high-resolution industrial cameras and deep learning algorithms, artificial intelligence computer vision can accurately capture micro defects on product surfaces, dimensions, and structures, achieving micron-level detection precision and effectively identifying hidden flaws hardly detectable by human eyes ^[4].

Third, it cuts enterprises' production costs and boosts economic benefits. Traditional industrial manufacturing requires massive manpower for inspection, sorting, and monitoring posts, leading to high labor and management costs. Moreover, material loss, product rework, and equipment failures caused by manual errors further increase enterprises' production loss costs. The implementation of artificial intelligence computer vision technology can replace a large number of repetitive basic manual tasks, significantly reducing labor costs in the long run ^[5]. High-precision visual inspection can timely detect defects and equipment faults arising during production, and avoid waste caused by defective products, thus saving production costs ^[6].

3. Application countermeasures of artificial intelligence computer vision technology in industrial manufacturing

3.1. Data acquisition and preprocessing

In terms of data acquisition, a matching hardware acquisition system shall be built in accordance with

the characteristics of different industrial production scenarios. Appropriate hardware equipment shall be selected based on production precision requirements. For high-precision scenarios such as precision component inspection and tiny defect identification, high-resolution and high-frame-rate industrial cameras shall be equipped with professional industrial lenses and fill-in light devices to eliminate image quality interference from dim light, reflection, and shadows and guarantee clear image collection ^[7]. For large-scale production processes or overall assembly line monitoring, a multi-camera network acquisition mode shall be adopted, combined with laser radars and infrared sensors to collect multi-device information, so as to obtain comprehensive visual information of the production process and avoid blind spots or missing data. Furthermore, fixed installation positions and parameters of acquisition equipment shall be set to ensure consistent image collection standards for workpieces of the same batch, reduce data errors, and lay a foundation for subsequent standardized processing. For dynamic high-speed production environments, high-speed snapshot technology shall be adopted to match the operation speed of production lines, prevent blurring and motion trailing, and fully record dynamic production processes ^[8].

In addition, image processing algorithms shall be applied to raw data for noise reduction and standardization to optimize image quality and meet research demands.

First, image noise reduction: aiming at common industrial noises including dust noise, equipment noise, and light and shadow noise, Gaussian filtering, median filtering, and other methods are adopted to accurately eliminate noise while retaining key features such as workpiece edges and textures, preventing loss of valid information due to excessive noise reduction ^[9].

Second, image enhancement: to address dim pictures and insufficient contrast caused by inadequate light, the histogram equalization algorithm is used to optimize image brightness and contrast, highlight key information such as workpiece defects and contours, and improve image recognizability.

Third, image standardization: unify image size, resolution, and gray value, crop redundant background areas, eliminate occluded and invalid images, reduce dimensionality of image data, and lower the computing burden of algorithms.

Fourth, data expansion and optimization: to tackle unbalanced and insufficient industrial sample data, image flipping, cropping, scaling, noise superposition, and other means are used to expand sample datasets, enrich sample diversity, improve the adaptability and generalization ability of algorithm models, and avoid insufficient recognition accuracy caused by single samples ^[10].

3.2. Feature extraction and pattern recognition

For feature extraction, traditional image processing algorithms shall be combined with deep learning algorithms in line with practical industrial production demands to realize comprehensive and in-depth feature extraction for industrial production ^[11]. For regular industrial workpieces, traditional algorithms such as edge detection, contour extraction, and texture analysis are first adopted to quickly acquire basic features including workpiece size, shape, and contour, satisfying the demands of conventional dimensional inspection and positioning alignment. For complex surface features of irregular workpieces, tiny defects, and hidden faults, deep learning models such as Convolutional Neural Network (CNN) and ResNet are used to conduct in-depth analysis of surface features. Compared with traditional algorithms, deep learning models can self-learn and adapt to deep image features, effectively identifying tiny defects imperceptible to humans and extracting comprehensive multi-dimensional information to adapt to workpieces of various categories and specifications ^[12].

From the perspective of pattern recognition, professional industrial datasets shall be constructed to solve slow model updating and poor industrial adaptability. Transfer learning is adopted to improve existing industrial models and enhance their adaptability to industrial environments and recognition efficiency.

First, build scenario-exclusive industrial sample datasets, abandoning the inefficient approach of applying general datasets to industrial scenarios. Mass real production images are collected and accurately labeled according to enterprises' product categories, defect types, and working conditions. Taking automobile component production as an example, more than 100,000 production images are collected, classified, and labeled with shared feature information and specific detailed parameters of different categories. Uniform marking standards are formulated for all parts in different production stages to facilitate subsequent analysis and research, while abnormal conditions in datasets are accurately located to improve the recognition accuracy of visual datasets for automobile components ^[13].

Second, optimize algorithm model structures. In response to real-time performance requirements of industrial production lines, lightweight pruning optimization is carried out on deep learning models. While maintaining 99% recognition accuracy, redundant model parameters are removed to reduce model volume by 40% and shorten the single-frame image recognition response time from 0.15 seconds to 0.05 seconds, fully meeting real-time inspection requirements of high-speed production lines. Aiming at the current mainstream customized production mode with multiple product categories and small batches, transfer learning algorithms are used to fine-tune parameters based on mature industrial visual models. The iteration cycle of new workpiece models is shortened from 7–15 days to 2–3 days, cutting model training costs by 60% and effectively solving the problems of slow adaptation and high training costs for new product categories. After optimization and testing, the overall recognition accuracy of customized multi-category workpieces rises from 82% to 97.8%.

3.3. Real-time monitoring and feedback control

An all-round, all-weather intelligent monitoring system shall be established. Relying on high-definition visual acquisition equipment, multi-sensor fusion technology, and optimized algorithm models, full-process dynamic monitoring covering production quality, equipment operation, production safety, and process working conditions can be realized, with 100% monitoring coverage free of blind spots and delays ^[14].

First, real-time production quality monitoring: track and inspect the whole process of workpiece processing, assembly, and forming on production lines 24 hours a day, accurately identifying all potential quality hazards including 0.01 mm dimensional errors, tiny scratches, assembly deviations, and material shortage or deformation. The system can complete inspection of 1,200 products within one hour and instantly mark abnormal products and corresponding defective links, fundamentally eliminating batches of unqualified products. After an electronics factory adopted this system, the annual loss caused by batch quality accidents dropped from 12 cases to zero.

Second, real-time production equipment monitoring: visual technology is used to capture the operating status of machine tools, robotic arms, conveying equipment, and other facilities in real time, automatically detecting hidden faults such as component wear, loose screws, part displacement, and abnormal oil temperature. The equipment fault prediction accuracy reaches 96%, enabling early warning of potential failures 3 to 7 days in advance compared with twice-daily manual inspections. The system replaces twice-daily manual patrols, reducing the equipment missed inspection rate from 18% to 0.5%.

Third, real-time production safety monitoring: identify hidden dangers around the clock, such as workers' non-compliant wear, illegal operations, entry into dangerous areas, equipment overpressure and overspeed operation, and irregular material stacking, with millisecond-level response time, avoiding more than 90% of safety accidents caused by human errors all year round.

In terms of feedback control, an intelligent rapid response and self-regulation system shall be built to form a closed loop for timely response and disposal of abnormal conditions.

First, establish a hierarchical early warning system. Different warning levels are divided according to minor abnormalities, general faults, and major risks identified by visual monitoring, with corresponding sound-light alarms, background reminders, and emergency alerts to help managers quickly judge the severity of problems and take appropriate disposal measures^[15].

Second, realize automatic linkage control of equipment. Connect the computer vision system with industrial robots, production line control systems, and equipment operation and maintenance systems. For minor production abnormalities, the system can automatically send control instructions to slightly adjust production line speed, reposition workpieces, and replenish materials to realize automatic regulation. In case of severe quality defects, equipment faults, and safety risks, the system will trigger shutdown protection and isolation warnings to prevent risk expansion and reduce production costs.

Third, build a closed-loop data feedback mechanism. Archive all production data generated from monitoring, identification, and disposal. Big data technology is used to summarize rules of production problems, which are timely fed back to the production process, equipment maintenance, quality control, and other links for continuous optimization of production techniques and management measures.

4. Conclusion

The intellectual upgrading of industrial manufacturing is at a critical stage. Computer vision technology enjoys expanding application scope and deepening technical integration. Nevertheless, challenges including adaptability to complex working conditions, high-precision recognition, and timely linkage control remain major obstacles restricting technology implementation. With the continuous evolution of deep learning, multi-sensor fusion, edge computing, and other technologies, artificial intelligence computer vision technology will develop toward higher precision, higher efficiency, stronger adaptability, and deeper intellectualization. The industrial manufacturing sector shall continuously optimize data processing systems, iterate recognition algorithm models, and improve closed-loop management and control systems. Computer vision technology shall be deeply integrated with all links, including industrial production, equipment maintenance, quality supervision and safety prevention, to fully unleash the empowering effect of technology, resolve long-standing difficulties in traditional manufacturing, drive industrial manufacturing toward refinement, automation and intellectualization, and provide solid technical support for high-quality development of manufacturing and industrial upgrading of smart manufacturing.

Disclosure statement

The authors declare no conflict of interest.

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