# Industrial Defect Detection Based on Computer Vision

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**Abstract.** To address the numerous limitations of traditional industrial defect detection, this paper reviews the current research condition of computer vision in the field of industrial defect detection. It summarizes the current technical bottlenecks and development trends. This study takes multiple typical industrial scenarios as the research objects, and conducts an analysis around technical principles and applications. It makes a detailed comparison between traditional and deep learning techniques, analyzes multi-industry applications, datasets, and evaluation systems, and distills the core challenges at both the technical and implementation levels, providing a reference for research and implementation in this field.

**Keywords:** Computer Vision, Industrial Defect Detection, Deep Learning, Machine Vision

## 1 Introduction

During the industrial production process, product defects have a direct and crucial impact on production quality, efficiency, and safety. The traditional manual defect detection methods have many unavoidable problems, such as low detection efficiency, susceptibility to subjective judgment interference, persistently high missed detection rate, and the ongoing reality of rising labor costs. Against this backdrop, computer vision technology, with its advantages of automation, high precision, and strong adaptability, demonstrates outstanding application value and development potential in the field of industrial defect detection.

The application and development of computer vision in the field of industrial defect detection has gone through three main stages: initially, it was centered on traditional machine vision methods, and the detection process was highly dependent on manual design of features and classic classifiers; subsequently, it entered a development stage driven by deep learning, leveraging the automatic feature learning ability of models, which significantly improved the detection accuracy and generalization performance; currently, the research focus in this field is gradually evolving towards lightweight, real-time, and multimodal integration directions. Small sample defect recognition, adaptation to complex scenarios, and algorithm deployment on edge devices have become the current research hotspots, and the overall trend is towards more intelligent, efficient, and practical development.

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This article focuses on computer vision technology as the research subject, selecting typical industrial scenarios such as electronic components, metal materials, and photovoltaic panels as the research objects. It conducts a systematic analysis around the technical principles, application practices, performance comparisons, and existing problems. Subsequently, it will elaborate on the basic theories, core algorithm advancements, industry application cases, data sets and evaluation methods in this field, and analyze the main challenges currently faced, as well as outline the future research directions.

This article is based on computer vision technology and covers industrial scenarios such as electronic components and metal materials. It analyzes the technical principles and application practices in these aspects. It comprehensively expounds the basic theories, core algorithms, and industry applications in this field, and also analyzes the existing challenges and future prospects.

## 2 Research on core technologies of computer vision in industrial defect detection

### 2.1 Traditional computer vision inspection technology

The core technical process of traditional computer vision detection technology is as follows: Firstly, through image preprocessing, the contrast of the defect area is enhanced; then, based on manually designed feature descriptors such as texture, edge, and shape features, defect information is extracted; finally, these features are input into traditional classifiers to complete the identification and classification of defects.

In terms of the classification of key technologies and the current research status, in the preprocessing techniques, methods such as mean filtering [1], median filtering [2], Gaussian filtering [3], histogram equalization [4], and edge enhancement [5] each have their own advantages. For instance, median filtering is good at eliminating salt-and-pepper noise, while Gaussian filtering is suitable for Gaussian noise environments. In terms of manual feature extraction, the gray-level co-occurrence matrix (GLCM) [6], edge detection operators such as Sobel/Canny/Laplacian, and morphological operations are widely used. Although these features have small computational costs and are easy to implement, they are sensitive to changes in lighting and object posture, and have limited generalization ability. In the classification and recognition stage, support vector machines (SVM) [7], backpropagation (BP) neural networks [8], Bayesian classifiers, or K-nearest neighbor (KNN) algorithms are often used. They still have applications in detection scenarios such as simple scratches on metal surfaces or stains on printed materials.

The advantages of traditional technologies lie in low computational cost, low deployment cost and good real-time performance. However, their core bottleneck is also quite obvious: insufficient generalization ability, making it difficult to handle complex and variable defect types; the feature design is highly dependent on expert experience, and it has high requirements for the stability of the detection environment. Currently, these methods are mostly applied in low-end industrial scenarios with relatively simple detection requirements, and their limitations have also given rise to the objective need for upgrading to more advanced technologies.

### 2.2 Industrial defect detection technology driven by deep learning

The classification model based on convolutional neural networks is currently the mainstream in defect classification technology. When dealing with the problem of imbalanced industrial defect samples and small sample sizes, attention mechanisms can be introduced for feature fusion or strategies such as transfer learning and contrastive learning can be employed to enhance generalization ability.

The target detection algorithms are mainly divided into two categories: two-stage detection methods (such as Faster R-CNN [9], Mask R-CNN [9]) and one-stage detection methods (such as YOLO series, SSD, RetinaNet [10]). Small sample defect detection (such as Few-Shot YOLO) and weakly supervised learning (reducing the reliance on annotations) are current cutting-edge directions, and related technologies have been applied in the detection of vehicle body scratches, photovoltaic panel cracks, etc.

Models such as FCN, U-Net, SegNet, and the DeepLab series of semantic segmentation algorithms can achieve pixel-level defect localization. When dealing with industrial defect edges that are blurry and have complex shapes, improved models like U-Net++ and attention U-Net have been proposed to enhance the segmentation accuracy and edge fitting effect. This technology is of great value in scenarios where precise acquisition of defect shapes and positions is required, such as metal surface cracks and internal bubbles in glass.

Multimodal fusion technology combines image information from different modalities such as visible light, infrared, and X-rays, providing new ideas for detecting internal cracks in metals and internal defects in electronic components. For edge devices in industrial fields with limited computing power, research on model lightweighting (such as improvements based on MobileNet and ShuffleNet) and deployment optimization (quantization, pruning) is gradually deepening. Moreover, to address the problem of scarce labeled data, exploration of self-supervised and semi-supervised learning methods has gradually become a research hotspot.

The core advantage of deep learning-driven industrial defect detection technology lies in its powerful feature learning and generalization capabilities, which can adapt to various complex defect types. However, its reliance on large-scale labeled data, high computational costs, deployment difficulties on edge devices, and performance degradation in small sample scenarios remain significant bottlenecks that need to be overcome. Compared with traditional technologies, deep learning undoubtedly remains the absolute research mainstream in the current and future periods.

## 3 Analysis of typical application scenarios of computer vision in industrial defect detection

In the defect detection of electronic components, high-precision and high-real-time detection of minor defects such as short circuits, open circuits, and pin deformations on chips and circuit boards is carried out. The widely used models include deep learning object detection (such as the YOLO series) and classification models (such as ResNet). However, how to further improve the detection rate of minor defects remains the main challenge in practical applications.

In the field of defect detection for metal materials, traditional edge detection methods are still applicable for surface scratches, cracks and internal defects of steel plates and steel pipes, etc. However, based on deep learning segmentation methods such as U-Net and multi-modal fusion technologies using visible light and infrared images are becoming mainstream. The reflective properties of metal surfaces and the low contrast between defects and backgrounds are the main challenges in technology adaptation.

In the field of defect detection for photovoltaic and semiconductor products, the detection of cracks in photovoltaic panels and defects in semiconductor wafers requires extremely high precision and large-scale rapid screening capabilities. Detection and segmentation algorithms based on deep learning, combined with special imaging techniques such as X-rays, play a crucial role in this area. The research focus is on how to balance detection accuracy and processing speed to meet the production line's cycle requirements.

In other typical scenarios, such as the textile, printing, automotive parts, and glass products industries, computer vision inspection technology has also been widely applied. For instance, fabric defect classification based on the improved ResNet, and the detection of appearance defects of automotive parts using the YOLO algorithm all demonstrate the adaptability and value of the technology in different contexts.

By comparing various application scenarios, the detection requirements and defect characteristics in different industrial scenarios vary, resulting in different technical focuses for their adaptation. However, issues such as small sample learning, robustness in complex environments, and real-time lightweighting are common technical challenges faced by all scenarios, and they are worthy of targeted research across different fields.

## 4 The dataset and performance evaluation for industrial defect detection using computer vision

At present, there are some publicly available datasets, such as NEU-DET (metal surface defect), PCB defect dataset, ELPV (photovoltaic defect), DAGM and KolektorSDD, etc. Among them, NEU-DET is a metal surface defect dataset constructed by Northeastern University, containing 1800 grayscale images of 6 typical defects of hot-rolled steel plates, with pixel-level mask annotations, and is a classic benchmark for the verification of metal defect detection algorithms; the PCB defect dataset is represented by DsPCBSD + , containing over ten thousand images of 9 types of PCB defects, with bounding box annotations covering minor defects such as short circuits and pin deformation, suitable for the training of circuit board detection algorithms; ELPV is a dedicated dataset for photovoltaic defect detection, containing 2624 EL images of photovoltaic modules, covering defects such as hidden cracks and broken grids, and a dual annotation system supports multi-task research; DAGM 2007 was released by the German Pattern Recognition Association and is designed for weakly supervised learning, containing 10 types of artificially synthesized industrial defects, only providing whole-image level annotations, suitable for algorithm verification under low annotation information; KolektorSDD focuses on surface defects of aluminum profiles , with 366 high-resolution color images containing two types of defects, scratches and pits, with the characteristics of small samples and pixel-level annotations, becoming an important test benchmark for small sample defect detection algorithms. These datasets have different scene focuses and provide key support for algorithm research and model training in the field of industrial defect detection.

However, there are common problems such as limited sample size, single type of defects, and a gap from actual industrial scenarios. Private datasets are constrained by high annotation costs and difficulty in sharing, which hinder the progress of research. Building datasets that are closer to reality, larger in scale, and with higher annotation quality, and exploring the use of semi-supervised methods to reduce annotation costs, are important directions for the future.

## 5 Existing problems and challenges

### 5.1 Technical challenges

In industrial scenarios, defect samples are scarce and unevenly distributed, resulting in insufficient generalization ability of the model, especially for small defects. The complex on-site environment (lighting changes, noise, product pose variations) imposes extremely high requirements on the robustness of the algorithm. There is a contradiction between the computational complexity of deep learning models and the high real-time requirements of industrial production lines (such as $\geqslant$ 30 FPS). Moreover, high-quality defect annotations are highly specialized and costly, severely restricting the development of data-driven models.

### 5.2 Challenges at the application implementation level

Some of the research work is disconnected from the actual complex conditions in industrial sites, resulting in the algorithms being merely theoretical and difficult to implement. The visual inspection system needs to be deeply integrated with the existing production lines and control systems, and the system integration involves many engineering challenges such as compatibility and stability. The high costs of hardware (high-precision cameras, computing equipment) and research and development make many small and medium-sized enterprises hesitate. At the same time, the shortage of specialized talents who are proficient in both algorithms and processes also hinders the implementation and continuous optimization of the technology.

## 6 Conclusion

This article systematically reviews the research and application panorama of computer vision in the field of industrial defect detection, and conducts a comparative analysis of the two core technologies driven by traditional machine vision and deep learning. The former, although having low deployment costs and good real-time performance, has weak generalization ability and is suitable for simple detection scenarios; the latter, with its strong feature learning ability, has become the mainstream. It has adapted algorithms for classification, detection, and segmentation tasks, and has become a research hotspot in lightweighting and multimodal fusion directions. The article also analyzes the technical adaptation characteristics and implementation difficulties in multiple industries such as electronic components and metal materials, pointing out that there are issues such as insufficient quality of public datasets, disconnection between the evaluation system and industrial reality, as well as technical challenges such as small sample detection, robustness in complex environments, and difficulties in system integration, cost, and shortage of specialized talents for implementation. Overall, this field needs to break through from aspects such as algorithm optimization, dataset construction, and engineering implementation to promote the technology to develop in a more intelligent, efficient, and practical direction, and achieve a deep integration with industrial production lines.

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