Journal of Artificial Intelligence Practice (2025)
Clausius Scientific Press, Canada
DOI: 10.23977/jaip.2025.080318
ISSN 2371-8412 Vol. 8 Num. 3

A Review of the Applications of Machine Vision in Industrial Surface Defect Detection

Ranning Deng

School of Electronic and Information Engineering, University of Science and Technology Liaoning, Anshan, China
2840820473@qq.com

Keywords: Machine Vision; Industrial Surface Defect Detection; Object Detection; Semantic Segmentation; Datasets; Lightweight Deployment

Abstract: Surface defects of industrial products directly affect product quality, operational safety, and market competitiveness. Traditional manual inspection methods suffer from low efficiency, strong subjectivity, and high missed detection rates, which can hardly meet the high-precision and high-speed inspection requirements of modern industrial production. With the advantages of non-contact measurement, high automation, and stable detection results, machine vision technology has gradually become a core technical means in the field of industrial surface defect detection. This paper focuses on the surface defect detection scenarios of typical industrial materials such as metals, plastics, and glass, systematically sorting out the application logic and applicable scenarios of three core machine vision technologies: object detection, semantic segmentation, and image classification. It details the characteristics and application scopes of mainstream public datasets such as NEU-DET and MTM-Surface-Defect, and deeply analyzes the influence mechanisms of key factors such as illumination changes and material reflection on detection accuracy. Finally, centering on the real-time inspection needs of production lines, it looks forward to future development directions such as lightweight model deployment and multimodal data fusion. This paper aims to provide a comprehensive technical reference for researchers and engineers in the field of industrial surface defect detection, and promote the large-scale application and optimization upgrading of machine vision technology in industrial production.

1. Introduction

Against the background of the transformation and upgrading of the manufacturing industry, industrial product quality control has become a key link to enhance the core competitiveness of enterprises. As one of the most common quality problems of industrial products, surface defects—such as scratches on metal plates, bubbles on plastic parts, and cracks on glass products—not only reduce the appearance quality of products but also may cause potential risks such as insufficient structural strength and failure of sealing performance, and even endanger personal safety in severe cases. Therefore, efficient and accurate surface defect detection is an indispensable important link in the industrial production process.

Traditional industrial surface defect detection mainly relies on manual visual inspection. The detection results are highly dependent on the experience and sense of responsibility of operators, with obvious shortcomings. On the one hand, manual inspection is inefficient and difficult to adapt to the high-speed operation needs of modern production lines. Especially in large-scale mass production scenarios, fatigue is likely to lead to increased missed detection and false detection rates. On the other hand, manual inspection is highly subjective, and different operators have different judgment standards for defects, which cannot guarantee the consistency and objectivity of detection results. In addition, some industrial production environments (such as high temperature, high pressure, and high dust) pose potential hazards to human health, making the safety of manual inspection difficult to guarantee.

With the rapid development of computer vision, machine learning, image processing and other technologies, machine vision technology has emerged and gradually been applied in the field of industrial inspection. Machine vision technology acquires product surface images through image acquisition equipment, and uses computer algorithms to preprocess, extract features, and identify defects from the images, realizing automatic and intelligent detection of product surface defects. Compared with traditional manual inspection, machine vision inspection has significant advantages such as non-contact measurement, fast detection speed, high precision, and repeatable results. It can effectively overcome the limitations of manual inspection and meet the stringent requirements of modern industrial production for quality control.

At present, machine vision technology has been widely applied in many industrial fields such as metal processing, plastic molding, and glass manufacturing, and relevant research results are emerging continuously. However, the surface characteristics of different industrial materials vary greatly, defect types present diverse and complex features, and there are many uncertain factors in the industrial production environment, leading to many challenges faced by machine vision inspection systems in practical applications. Based on this, this paper conducts a review around the application of machine vision in industrial surface defect detection, systematically sorting out the core technology application logic, mainstream datasets, key technical challenges, and future development trends, so as to provide reference for technical research and engineering practice in this field.

2. Application Logic of Core Machine Vision Technologies in Industrial Surface Defect Detection

The core process of machine vision technology in industrial surface defect detection includes four links: image acquisition, image preprocessing, feature extraction, and defect recognition and classification. Among them, defect recognition and classification are the core of the entire detection system, mainly relying on three key technologies: object detection, semantic segmentation, and image classification. Different technologies have unique technical logic and applicable scenarios, and need to be reasonably selected according to industrial material characteristics, defect types, and detection requirements.

2.1 Application Logic of Image Classification Technology

Image classification technology is a basic core in machine - vision. Its logic is to judge input image categories by learning image features via algorithms. In industrial surface defect detection, it judges product - surface defects and classifies them (e.g., scratches, cracks).

The application process: First, build a dataset with normal and defect images, annotate and train the classification model. The trained model extracts key features (gray distribution, texture) and judges the image category by feature similarity. It suits scenarios with single - type defects, small defect areas, and low - precision defect location.

For metal materials, it detects rust and scratches as the surface is flat and defect features are obvious. For plastics, it detects bubbles and depressions with distinct gray and shape features. For glass, it detects scratches and sand particles, especially useful in mass production for quick product screening.

Common models include traditional and deep - learning ones. Traditional models like support vector machines rely on manual features for simple scenarios. Deep - learning models such as AlexNet automatically extract deep features, have strong learning and generalization abilities, and are the mainstream for industrial defect classification.

2.2 Application Logic of Object Detection Technology

On the basis of image classification technology, object detection technology realizes defect positioning and category judgment. Its core is to identify defect area coordinates and determine defect categories via algorithms, outputting three key defect information: "existence", "type", and "location", meeting industrial inspection's defect - positioning demand.

The application process: after getting the product surface image, the model extracts features, traverses the image using methods like sliding windows and anchor mechanisms to check for defects, marks defect areas with bounding boxes, and outputs defect categories and box coordinates. This technology suits scenarios where defect positions are unfixed and needs clarification, and has wide industrial application.

In the metal processing industry, it detects scratches, pits, and weld defects on steel plates and pipes, providing references for repair[4]. In plastic molding, it detects flash, missing material, and bubbles on injection - molded parts, especially for complex - shaped plastic parts, avoiding manual inspection misses. For glass products, it locates cracks, stones, and scratches for quality grading.

Mainstream object detection models fall into two categories. Two - stage models based on region proposals, like Faster R - CNN, generate candidate regions first and then classify and regress bounding boxes, with high accuracy but slow speed. Single-stage models based on regression, such as YOLO and SSD, can complete detection and positioning in one image traversal, with fast speed for real - time detection[1].

2.3 Application Logic of Semantic Segmentation Technology

Semantic segmentation technology is the most accurate defect detection method in machine vision technology. Its core logic is to divide each pixel in the image into corresponding categories (such as background, normal area, and specific type of defect area), realizing pixel-level accurate segmentation of defect areas. This technology can clearly present detailed information such as the shape, size, and boundary of defects, providing support for quantitative analysis of defects.

The application process of semantic segmentation technology is as follows: the model performs pixel-level feature extraction on the input product surface image, gradually refines the feature map through network structures such as encoder-decoder, and finally outputs a segmentation map consistent with the size of the input image, where different colors or gray values represent different categories. This technology is suitable for detection scenarios with high requirements for defect morphology and size accuracy, especially having an irreplaceable advantage in industrial scenarios that require quantitative evaluation of defects.

In the field of precision metal processing, semantic segmentation technology can be used to detect microcracks, tiny scratches, and other defects on the surface of precision instrument parts. Through pixel-level segmentation, it can accurately measure parameters such as the length, width, and area of defects, providing accurate data support for part quality evaluation. In the glass manufacturing industry, this technology can be used to detect tiny cracks and impurities on the surface of ultra-thin glass. These defects are small in size and have fuzzy boundaries, and semantic segmentation technology can effectively distinguish defect areas from normal areas[5]. In the production process of plastic films, semantic segmentation technology can detect defects such as pinholes, impurities, and uneven thickness on the film surface. By accurately segmenting defect areas, it realizes quantitative analysis of defects and optimization of production processes.

Common semantic segmentation models include FCN, U-Net, SegNet, etc. Among them, U-Net and its improved models are most widely used in industrial surface defect detection due to their good semantic information retention ability and segmentation accuracy[2]. Such models extract image features through encoders and restore image resolution through decoders, which can achieve high-precision segmentation results on limited datasets, suitable for the situation of scarce defect samples in industrial scenarios.

3. Mainstream Public Datasets for Industrial Surface Defect Detection

Datasets are the foundation for training and evaluating machine vision models. High - quality datasets can improve model accuracy and generalization. For industrial surface defect detection, many public datasets have been built, covering various materials and defect types. Here is an introduction to the mainstream ones.

The NEU - DET dataset, built by Northeastern University, is for hot - rolled steel plate defect detection. It has 6 defect types, 300 images per type (1800 in total), shot at industrial sites with 200×200 resolution. It includes defect annotations and is a benchmark in metal defect detection.

The MTM - Surface - Defect dataset covers metals, plastics, and ceramics. It has 8 defect types, 2400 images in total (800 per material, 300 per defect type), with 512×512 resolution. It's suitable for cross - material model training and provides detailed annotations for different tasks.

The DAGM dataset, constructed by the German Association for Pattern Recognition, focuses on metal and plastic defect detection. It has 10 defect categories, 1000 training and 200 test images per category, with 512×512 resolution. Defects are generated by simulation, suitable for standardized scenario evaluation and algorithm assessment.

The Magnetic Tile Defect Dataset is for magnetic tile defect detection. It has 6 defect types, 3172 images (2626 training, 546 test), collected on - site with 600×600 resolution. It has diverse and complex defects, suitable for high - robustness model training.

The Glass Surface Defect Dataset is for glass defect detection, covering 5 defect types, with 1500 images and 800×600 resolution. Images are shot in real production, reflecting glass material characteristics. It provides annotations for multiple tasks.

Besides these, there are targeted datasets like the Steel Surface Defect Dataset for cold - rolled steel plates and the Plastic Defect Dataset for plastic parts. While these datasets support industrial defect detection development, they have limitations such as small scale, single defect types, and lack of complex environment data. Future efforts should enrich dataset diversity and authenticity.

4. Key Technical Challenges in Industrial Surface Defect Detection

Although machine vision technology has made significant progress in industrial surface defect detection, in practical industrial application scenarios, affected by various factors such as environmental factors, material characteristics, and defect diversity, the accuracy and stability of detection systems still face many challenges, restricting their large-scale application in some high-end manufacturing fields.

Illumination change is the primary environmental factor affecting the accuracy of machine vision detection. The illumination conditions in industrial production sites are complex and variable.

Changes in the intensity of natural light and deviations in the angle of artificial light sources will cause changes in the gray distribution of product surface images, thereby affecting the extraction and recognition of defect features. For metal materials, changes in illumination angle will cause changes in the position and intensity of reflective areas on the surface, which may misjudge reflective areas as defects or cover up real defect areas. For glass materials, the transparent characteristic makes changes in light transmittance affect the contrast of defects in images, making it difficult to identify tiny defects. The surface roughness of plastic materials varies, and their reflection characteristics to light are also different. Illumination changes are likely to cause blurred boundaries between defects and backgrounds, increasing the difficulty of recognition. In addition, light sources in some industrial production scenarios (such as workshop assembly lines) may experience aging and brightness attenuation due to long-term use, further exacerbating the impact of unstable illumination on detection accuracy.

Material reflection characteristics are one of the core technical difficulties in industrial surface defect detection. The surface physical characteristics of different industrial materials vary greatly. The surface of metal materials is smooth and has strong specular reflection characteristics, which are prone to produce highlight areas, leading to the masking of defect features. Glass materials have dual characteristics of transparency and reflectivity. The reflection and refraction of light will cause false defect signals in images, interfering with the recognition of real defects. Some plastic materials (such as polyethylene and polypropylene) have a certain gloss on the surface, and the reflection intensity is greatly affected by the observation angle, which also affects the accuracy of defect detection. To solve the problem of material reflection, existing methods mainly reduce the impact of reflection by adjusting the light source angle, using polarized light sources, and performing image preprocessing. However, in complex industrial scenarios, the effect of these methods is still limited, and it is difficult to completely eliminate the interference of reflection on detection accuracy.

Defect diversity and complexity are important factors restricting the generalization ability of detection systems. There are many types of defects in industrial products. The defect morphologies corresponding to different production processes and materials are significantly different. Even for the same type of defect, its shape, size, position, and gray features may vary greatly. For example, scratches on metal plates may be linear or curved, with lengths ranging from a few millimeters to tens of millimeters. Bubbles on plastic parts may be a single large bubble or multiple tiny bubbles aggregated. Cracks on glass products may be through cracks or surface tiny cracks. In addition, some defects have hidden characteristics, such as tiny slag inclusions on metal surfaces and bubbles inside plastics, which have low contrast with normal areas in images and are difficult to be identified. The diversity and complexity of defects make it difficult for a single machine vision model to adapt to all scenarios, and the generalization ability of the model faces great challenges.

Background interference and noise pollution will seriously affect the extraction accuracy of defect features. The surface of industrial products may have background information such as natural textures and processing traces. These background information may be similar to defect features, leading to model misjudgment. For example, natural textures such as wood textures and fabric textures may be misjudged as scratch defects. Processing traces such as tool marks and indentations generated during metal processing may be confused with real defects. In addition, noise is inevitably introduced during image acquisition, such as camera sensor noise and electromagnetic interference noise during transmission. These noises will destroy the integrity of defect features, leading to blurred boundaries and distorted features of defect areas, thereby reducing detection accuracy.

The contradiction between real-time detection requirements and model complexity is an important challenge in industrial scenario applications. The operation speed of modern industrial production lines is constantly increasing, putting forward strict requirements for the detection speed of defect detection systems, which usually need to reach a detection speed of several frames or even dozens of frames per second. However, high-precision machine vision models (such as complex semantic segmentation models and two-stage object detection models) usually have high computational complexity, requiring a lot of computing resources and time, and are difficult to meet real-time detection requirements. How to reduce the computational complexity of the model on the premise of ensuring detection accuracy and realize lightweight deployment is the core contradiction faced by machine vision technology in industrial assembly line surface defect detection.

5. Future Development Prospects

With the in-depth advancement of Industry 4.0, industrial production has put forward higher requirements for the accuracy, speed, and intelligence level of surface defect detection. The application of machine vision technology in this field will develop towards lightweight, multimodal fusion, intelligence, and large-scale directions.

Lightweight model deployment will become the core development direction of real-time detection in industrial assembly lines. To solve the contradiction between model complexity and real-time detection requirements, lightweight technology reduces the number of model parameters and computational complexity through methods such as model compression, quantization, pruning, and knowledge distillation, and improves the inference speed of the model on the premise of ensuring detection accuracy. In the future, for specific scenarios of industrial surface defect detection, special lightweight models will be further developed. Combined with edge computing technology, the deployment of detection models on edge terminals such as industrial cameras and embedded devices will be realized, reducing data transmission delay and meeting the real-time detection requirements of assembly lines. At the same time, the transfer learning technology of lightweight models will be further developed. Through pre-training on large-scale datasets and then fine-tuning on small datasets of specific industrial scenarios, the rapid adaptation and deployment of models will be realized.

Multimodal data fusion technology will effectively improve detection accuracy in complex scenarios. Single visual data is easily affected by factors such as illumination, reflection, and background interference. Multimodal data fusion technology can obtain more comprehensive and rich defect information by fusing visual data with other sensor data (such as infrared data, ultrasonic data, lidar data), improving the robustness of defect recognition[6]. For example, infrared data can reflect the temperature distribution difference on the product surface, which can effectively identify internal cracks of metal materials. Ultrasonic data can penetrate the material surface to detect internal defects[3]. Lidar data can provide 3D contour information of the product surface, facilitating accurate measurement of the depth and volume of defects. In the future, machine vision detection systems based on multimodal data fusion will become an important development trend in the field of high-end manufacturing. Through the complementary advantages of multi-source data, the defect detection problems in complex industrial scenarios will be solved.

Data augmentation and semi-supervised learning technologies will alleviate the problem of scarce defect samples. In industrial scenarios, high-quality annotated defect samples are usually difficult to obtain, leading to limited model training. Data augmentation technology artificially expands the number of training samples through methods such as image rotation, flipping, scaling, noise addition, and illumination transformation, improving the generalization ability of the model. Semi-supervised learning technology uses a large number of unlabeled samples and a small number of labeled samples for model training, reducing the dependence on labeled samples. In the future, more targeted data augmentation methods will be developed according to the characteristics of industrial surface defects, such as random generation of defect areas and combined splicing of different defect types. At the same time, the combination of semi-supervised learning with transfer learning and reinforcement learning will become a research hotspot, further improving the detection performance of models in small sample scenarios.

The deep integration of intelligent detection and production processes will realize closed-loop optimization of quality control. Future machine vision detection systems will not only be able to realize automatic identification and classification of defects but also have intelligent functions such as defect cause analysis and production process optimization suggestions. By constructing a correlation model between defect types and production process parameters, the detection system can reversely infer potential problems in the production process (such as poor raw material quality, abnormal equipment parameters, unreasonable processing technology, etc.) according to information such as the type, position, and frequency of defects, and provide data support for production process optimization. This closed-loop model of "detection-analysis-optimization" will realize the whole-process control of product quality, fundamentally reduce the defect rate, and improve the intelligence level of industrial production.

Standardization and large-scale application will promote industrial development. At present, there is a lack of unified technical standards and evaluation systems in the field of industrial surface defect detection. The detection systems of different enterprises have differences in data formats and model performance evaluation indicators, which is not conducive to the promotion and application of technology. In the future, the industry will gradually establish unified technical standards and evaluation systems, standardize the construction of datasets and the evaluation methods of model performance, and promote technical exchange and cooperation between different enterprises and research institutions. At the same time, with the maturity of machine vision technology and the reduction of costs, its application will extend from high-end manufacturing fields to mid-low-end manufacturing fields, realizing large-scale application and promoting the improvement of the quality control level of the entire manufacturing industry.

6. Conclusion

With the advantages of non-contact measurement, high automation, and stable detection results, machine vision technology has become a core technical means in the field of industrial surface defect detection, and has been widely applied in the defect detection of various materials such as metals, plastics, and glass. This paper systematically sorts out the application logic of three core machine vision technologies: object detection, semantic segmentation, and image classification, details the characteristics of mainstream public datasets such as NEU-DET and MTM-Surface-Defect, deeply analyzes key technical challenges such as illumination changes, material reflection, and defect diversity, and looks forward to future development directions such as lightweight deployment, multimodal fusion, and intelligent integration.

At present, machine vision technology has made significant progress in industrial surface defect detection, but it still faces many challenges, such as the need to improve detection accuracy in complex environments, the unresolved contradiction between real-time detection and model complexity, and the restriction of model performance by the problem of scarce defect samples. In the future, through the innovation and breakthrough of technologies such as lightweight model technology, multimodal data fusion, data augmentation, and semi-supervised learning, the performance of machine vision detection systems will be continuously improved, and gradually realize deep integration with industrial production processes, providing strong support for the high-quality development of the manufacturing industry.

Industrial surface defect detection is a key link to ensure product quality. The application and development of machine vision technology are of great significance for promoting the transformation and upgrading of the manufacturing industry. With the continuous progress of technology and the continuous expansion of application scenarios, the application of machine vision in the field of industrial surface defect detection will be more extensive and in-depth, injecting new vitality into the realization of intelligent, efficient, and high-quality development of industrial production.

References

[1] Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[2] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Cham: Springer international publishing, 2015.

[3] Wen, Qiaonong, and Shuang Xu. "Applications of Ultrasound Targeted Micro/Nano Probes and Intelligent Ultrasound Molecular Imaging Technology." Journal of Biomedical Nanotechnology 19.5 (2023): 689-705.

[4] Ma, Xiaolin, et al. "YOLOv7-BA: A Metal Surface Defect Detection Model Based On Dynamic Sparse Sampling And Adaptive Spatial Feature Fusion." 2024 IEEE 6th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC). Vol. 6. IEEE, 2024.

[5] He, Zhiyong, and Lining Sun. "Surface defect detection method for glass substrate using improved Otsu segmentation." Applied optics 54.33 (2015): 9823-9830.

[6] Wang, Haojie, et al. "Fiber optic sensing technology and vision sensing technology for structural health monitoring." Sensors 23.9 (2023): 4334.