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A Survey of Semi-supervised and Unsupervised Learning Methods for Industrial Defect Anomaly Detection

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Abstract

With the continuous advancement of industrial automation, intelligent defect detection has become a crucial means of ensuring product quality. However, the cost and labor required to obtain high-quality labeled data limit the widespread practical application of traditional supervised learn-ing methods. Therefore, semi-supervised learning (SSL) and unsupervised learning (UL) methods have received extensive attention from researchers due to their superior performance in low-labeled or unlabeled scenarios. This paper provides a systematic survey of typical semi-supervised and unsupervised learning methods in the field of industrial defect detection, analyzes the core concepts and key technologies of unsupervised learning and semi-supervised learning, as well as compara-tive analysis on relevant datasets, and finally proposes future development directions.

Keywords

Industrial defect detection; Unsupervised learning; Semi-supervised learning; Deep learning; Anomaly detection; Quality control

1. Introduction

Industrial surface defect detection is an important component of modern manufacturing quality assurance systems, widely applied across various fields including steel metallurgy, textile and apparel, semiconductor manufacturing, and automotive industry. From aircraft to chips, accurate and efficient defect detection not only enables timely identification of product quality issues and prevents defective products from entering the market, but also provides data support for production process optimization, thereby improving overall production efficiency and product quality. With the rapid development of Industry 4.0 and intelligent manufacturing, automated quality inspection has become a core requirement of modern manufacturing. Therefore, industrial defect detection has emerged as a key technology in intelligent manufacturing and automated production, with extensive applications in unmanned quality inspection, intelligent detection, and other fields.

However, industrial anomaly detection faces numerous challenges. For example, defects come in various types, and traditional manual visual inspection methods suffer from low efficiency, strong subjectivity, and high costs, making it difficult to meet the quality control requirements of large-scale production.

This paper aims to systematically review unsupervised and semi-supervised deep learning methods in industrial defect detection, providing researchers and practitioners with a comprehensive technical overview and development trend analysis. The paper is structured as follows: Section 2 presents the research background; Section 3 discusses detection methods; Section 4 covers semi-supervised learning; Section 5 introduces public datasets and evaluation metrics; Section 6 summarizes the entire paper and outlines future development directions.

2. Research Background

2.1. Problem Definition

Computer vision-based detection applications can be applied to the appearance of fabrics, solar cells, new energy battery surfaces, pharmaceuticals, steel materials, and construction materials. During the manufacturing process of industrial components, due to the influence of processing technology, raw material quality, and production environmental conditions, component surfaces frequently develop quality issues such as scratches, dents, oxide scale, and other anomalies [1]. These quality problems not only reduce the overall performance and quality level of components, but also negatively impact product reliability and service life. In severe cases, they may even lead to safety accidents, causing significant economic losses to manufacturing enterprises.

The concept of defects can be analogized to anomalies, where anomalies refer to data that exceeds the expected pattern range. Defects are other conditions that appear in normal objects, such as cracks, inclusions, patches, and scratches in steel materials; open circuits, short circuits, and foreign objects in PCB boards; and cracks, dark spots, and fractures in solar panels.

Industrial surface defects typically manifest as texture mutations, geometric deformations, or material anomalies. Their definitions can be categorized as: point anomalies where local pixel values deviate from the normal range; contextual anomalies where local patterns violate global rules; and cluster anomalies where regional correlations are abnormal, which can be explained as a series of related data collections where each instance's values fall within normal ranges when examined individually, but the overall correlation characteristics do not conform to normal patterns. For example, scratches on metal surfaces belong to point anomalies, while misalignment of fabric textures belongs to contextual anomalies.

At the semantic level, defect detection needs to distinguish between three levels of

tasks: classification (determining defect types), localization (identifying defect positions), and segmentation (pixel-level annotation).
Industrial defect detection can be formally defined as an anomaly detection problem. Given an industrial product image set $D = \{x_1, x_2, \ldots, x_n\}$, where $x_i \in \mathbb{R}^{H \times W \times C}$ represents a C-channel image with resolution $H \times W$. In the unsupervised learning scenario, the training set $\mathcal{D}_{train}$ contains only normal (defect-free) samples; in the semi-supervised learning scenario, the training set contains a large number of normal samples and a small number of labeled anomalous samples.

2.2. Problem Challenges

2.2.1. Data Challenges

1. Diverse varieties: Defect morphologies often exhibit irregular characteristics. Industrial products may simultaneously present multiple types of quality issues, and even the same type of quality problem shows significant differences in appearance, size, color, and other attributes. Traditional detection technologies can typically only identify fixed categories of quality issues. Currently, detection technologies need to possess comprehensive capabilities to identify various quality problems, ensuring that no potential issues are overlooked.
2. Uncertainty and subjectivity: The manifestation of defects is often unpredictable, making it difficult to achieve accurate direct characterization. Current defect types summarized through manual analysis still cannot cover all varieties, rendering many traditional detection methods ineffective when facing novel defects. Additionally, defect identification typically requires judgment based on specific application environments, introducing subjectivity and further increasing the complexity of data labeling work.
3. Noise: In the variable industrial manufacturing environment, standard sample data is often accompanied by contamination phenomena or noise signal interference. The instability of imaging environmental factors, such as fluctuations in lighting conditions, camera viewpoints, image scale, occlusion effects, imaging sharpness, and other parameters, can easily cause significant variations in the training dataset that should not originally be classified as defects.
4. Imbalanced distribution of training samples: In defect identification tasks, the unbalanced distribution of training data is a common challenge, mainly reflected in the distribution differences between image subjects and environments, presence or absence of defects, various defect types, and defect sizes, along with unstable factors in defect attributes and real environments. Considering the relative scarcity of defect instances, unsupervised learning strategies utilize intact samples for model construction, but the distribution uniformity of intact samples directly determines the model's effectiveness in locating abnormal regions. If specific types of normal

samples are missing from the training set, the model tends to incorrectly label such samples as abnormal.
5. Expensive data annotation: In industrial applications, data annotation typically requires significant time and labor investment, leading to high costs for image processing.

2.2.2. Task Challenges

1. High precision: Industrial anomaly detection has high precision requirements that must exceed human visual accuracy, demanding the reduction of missed detections and false alarms.
2. Low overhead: While current computer vision can provide high-resolution images, computational time, system overhead, and computational power requirements must be considered. For actual production manufacturing or intelligent inspection applications, achieving high-speed real-time detection operation has become one of the key research focuses.

2.3. Research Overview

Industrial defect detection has always been one of the most important research areas in the field of industrial vision. With the development of deep learning and its popularization in industrial fields, deep learning-based industrial defect detection methods have achieved rapid development. Benefiting from the feature extraction capabilities of convolutional neural networks and their ability to represent high-dimensional data, these methods have gradually replaced manual selection, significantly improving both detection accuracy and speed while solving the problem of labor costs. Compared to traditional image processing methods, deep learning-based image processing is more adept at handling complex industrial image data.
Industrial defect detection algorithms are divided into three modes based on scenarios: known defects, unknown defects, and few-shot defects. For known defect modes, supervised deep learning methods are generally adopted, requiring extensive sample annotation, and methods can be designed from three perspectives: classification, detection, and segmentation. For industrial anomaly detection of unknown defects, it is subdivided into pixel-level and feature-level approaches. For scenarios with limited defect annotations, which are more aligned with industrial production situations, there exist small amounts of defect samples with accurate or inaccurate annotations in actual industrial production processes. Based on this, semi-supervised learning and unsupervised learning methods can be adopted for processing.

2.4. Research Status

The development of industrial defect detection can be divided into the following stages:

First is the traditional image processing stage. Before deep learning, methods primarily used traditional approaches based on edge detection, texture analysis, morphological operations, etc. Main algorithms included Sobel operators, Gabor filters, Local Binary Patterns (LBP), etc. These methods had high computational efficiency but were sensitive to complex backgrounds and lighting variations, with limited performance in complex scenarios.

In the machine learning stage, machine learning algorithms such as Support Vector Machines (SVM) and Random Forest were introduced. Defect detection was achieved by combining manually designed features (such as HOG, SIFT) with traditional classifiers. Methods in this stage relied on expert experience for feature design and had limited generalization capabilities.

In the early deep learning stage, the successful application of CNNs brought breakthroughs in deep learning for industrial detection. Early approaches mainly adopted supervised learning methods, such as LeNet, AlexNet, VGG, and other network architectures. This stage significantly improved detection accuracy but heavily relied on large amounts of annotated data.

With the development of deep learning, supervised and unsupervised learning methods have been applied to industrial defect detection. Convolutional Neural Networks (CNNs) became the primary tool, capable of achieving high detection accuracy on large amounts of annotated data. However, these methods require extensive annotated data, while industrial defect data is difficult to obtain and costly.

Finally, in unsupervised learning, attention mechanisms and Graph Convolutional Networks have been introduced, combined with transfer learning and domain adaptation techniques to improve model generalization and adaptation capabilities. Although recent unsupervised and semi-supervised learning have made significant progress in this field, relevant literature has not systematically summarized these methods. This paper elaborates on unsupervised learning and semi-supervised learning methods in deep learning, providing reference for researchers and practitioners.

3. Detection Methods

3.1. Classification of Detection Tasks

Industrial defect detection tasks and challenges. Industrial defect detection typically includes the following tasks:

Defect Classification: Systematically categorizing defects based on their nature, type, or causation.

Defect Localization: Accurately determining the specific location of defects within the inspected object. Defect localization is a crucial step in the defect detection process, providing the foundation for subsequent defect segmentation and repair. Localization methods typically combine image processing techniques and computer vision algorithms to determine the spatial distribution of defects by analyzing detection data (such as microscopic images, photoelectric detection signals, etc.).

Defect Segmentation: Based on defect localization, defect segmentation precisely separates defect regions from the background to form defect contours or masks. Segmentation techniques typically employ image segmentation algorithms, such as threshold segmentation, edge detection, deep learning semantic segmentation, etc., to achieve fine extraction of defect regions.

3.2. Anomaly Score Calculation

Unsupervised and semi-supervised methods typically determine the degree of abnormality in samples by calculating anomaly scores. The calculation method for anomaly score $s(x)$ varies by approach:

Reconstruction error is expressed as $s(x) = \| x - \hat{x} \|_2$, wher $\hat{x}$ is the reconstructed image. Generation probability is expressed as $s(x) = \min_{f_j \in \mathcal{M}} \| f(x) - f_j \|_2$, where $p(x \mid \theta)$ is the learned probability distribution. Feature distance is expressed as $s(x) = \min_{f_j \in \mathcal{M}} \| f(x) - f_j \|_2$, where $\mathcal{M}$ is the memory bank of normal features.

Unsupervised methods can be divided into image similarity-based and feature similarity-based approaches.

Table 1. Classification of Unsupervised Learning Methods in Industrial Defect Detection

Grade	Class	Approach
Pixel	AE-based methods	Multi-scale, feature clustering, memory bank, self-supervised
	VAE-based methods	Constrained latent space, attention mechanism hybrid model
	GAN-based methods	Combining AE/VAE
Feature	Deep one-class classification	Constructing classification terms
	Siamese network architecture	Mapping to specific feature space
	Deep statistical template	Multivariate Gaussian distribution modeling
	Flow models	Regularized flow
	Teacher-student architecture	Knowledge distillation, reverse distillation

Table 2. Introduction of Semi-supervised Learning-based Methods

Core theoretical assumption	Classical methods	Deep learning methods
Smoothness assumption	Self-training	Consistency regularization
Cluster assumption	Collaborative training	Pseudo-label methods
Manifold hypothesis	Graph-based methods	Adversarial training
Generative assumption	Generative models	Generative models

3.3. Unsupervised Learning Methods

Based on technical principles and implementation methods, unsupervised industrial defect detection methods can be divided into five major categories: image reconstruction, generative models, deep feature embedding, self-supervised learning, and one-class classification methods.

3.3.1. Autoencoder Methods in Image Reconstruction

Autoencoders learn low-dimensional representations of data through an encoder-decoder architecture. The basic idea is that normal samples can be well reconstructed, while abnormal samples have larger reconstruction errors. Traditional autoencoders: The most basic AE consists of fully connected layers and is trained by minimizing reconstruction loss:

$$\mathcal{L} = \| x - \mathrm{Decoder}\left(\mathrm{Encoder}\left(x\right)\right) \|_2^2 \qquad (3.1)$$

This represents the loss function value, where x is the original data, Encoder(x) is the encoding process, and Decoder(Encoder(x)) is the complete reconstruction process.

AE learns a low-dimensional feature representation space and reconstructs data instances in this low-dimensional feature representation space. According to the formula, it consists of an encoder and a decoder. The encoder maps the original data to a low-dimensional space, while the decoder recovers data from the low-dimensional space, preserving important information during data reconstruction.

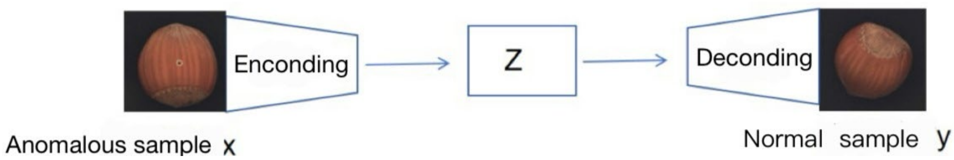

Figure 1. AE Architecture

3.2. Identify the Headings

Kang et al. [21] proposed a contact line component detection method based on Faster R-CNN. This method first utilizes Faster R-CNN to achieve precise component localization, then combines deep material classification networks and deep denoising autoencoder technology to complete component category identification and anomaly detection tasks.

In the field of industrial image processing, Youkachen et al. developed image reconstruction technology based on convolutional autoencoders. This method achieves effective image segmentation through the image reconstruction process, combined with sharpening processing technology to amplify the difference features between images.

Following this development, research on AE-based methods has made progress in multiple directions, such as multi-scale, memory bank, and multi-decoder approaches.

Multi-scale: Addressing the problem of large target scale differences in anomaly detection, multi-scale autoencoders capture feature information at different scales by constructing multiple encoding-decoding paths with different receptive fields. Mei et al. [47] reconstructed image patches at different Gaussian pyramid levels and synthesized detection results from different resolution channels, preserving structural information of images and enhancing model generalization capability by introducing artificial noise. By combining feature information at different scales, the detailed reconstruction capability is improved. The multi-scale fully convolutional autoencoder (MSAE) proposed by Mujeeb et al. achieved good results in fabric defect detection.

Memory bank: The core idea of memory banks is to introduce external memory mechanisms that store typical feature patterns of normal samples. The memory bank stores feature representations of normal samples, and during reconstruction, only features from the memory bank are used:

$$\hat{x} = \mathrm{Decoder}\left(\mathrm{MemoryBank}\left(\mathrm{Encoder}\left(x\right)\right)\right) \tag{3. 2}$$

Where Encoder(x) is the encoder, MemoryBank(•) is the memory bank, and Decoder(•) is the decoder.

Anomaly detection accuracy is enhanced through memory retrieval and matching. Gong et al. utilized an external memory module to record normal data patterns and used the memory module to reconstruct input data to achieve better results.

Multi-decoder: The core idea of multi-decoding is to use multiple parallel or cascaded decoder branches to reconstruct input data from different perspectives, improving anomaly detection performance through multiple constraints. The technical characteristics include: each decoder being responsible for reconstructing different types or levels of features, enhancing model stability through consistency constraints from multiple decoders, capturing multi-faceted information of data (such as texture, structure, semantics, etc.), and providing multiple reconstruction error metrics for comprehensive anomaly judgment.

Convolutional Autoencoder (CAE): Designed for image data, using convolutional layers and transposed convolutional layers as shown in the figure,

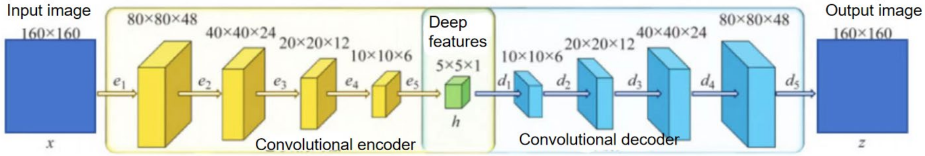

Figure 2. CAE Architecture

Where $e_1 \sim e_5$ represents the convolutional encoder, and $d_1 \sim d_5$ represents the convolutional decoder.

3.3.2 Variational Autoencoder (VAE)

VAE learns the probability distribution of data through variational inference and has stronger generative capabilities and theoretical foundation compared to traditional AE.

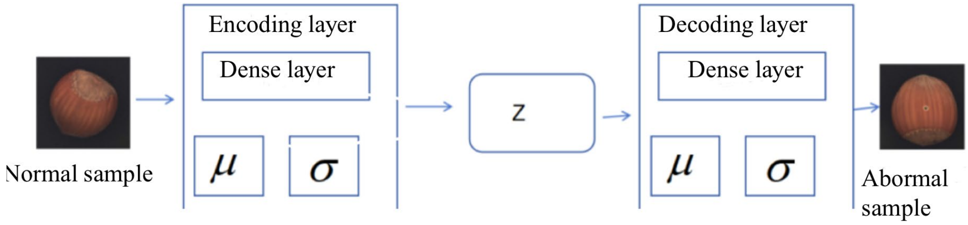

Figure 3. VAE Network Architecture

In basic VAE, the latent variable z is assumed to follow the prior distribution $p(z)=\mathcal{N}(0,I)$, and is trained by maximizing the variational lower bound:

$$\mathcal{L}=\mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x\mid z)]-D_{KL}(q_\phi(z\mid x)\Vert p(z)) \qquad (3.3)$$

Adversarial Variational Autoencoder (CAVGA): Combines GAN's discriminator to improve generation quality while maintaining VAE's probabilistic interpretability.

3.4. Deep feature embedding-based methods

These methods model normal data distribution in deep feature space, avoiding complex image reconstruction processes and typically achieving better detection accuracy and computational efficiency.

3.4.1. Student-Teacher networks

The basic idea is to use a pre-trained teacher network to extract features and train a lightweight student network to mimic the teacher network's behavior on normal samples. During testing, the student network cannot effectively mimic the teacher network's output on anomalous samples.

Uninformed Students: The classic student-teacher framework proposed by Bergmann et al., which uses multiple student networks to predict features from different layers of the teacher network

4. Semi-supervised learning methods

Semi-supervised learning methods combine a small amount of labeled data with a large amount of unlabeled data, significantly reducing annotation costs while maintaining high detection accuracy. This aligns with practical industrial scenarios where the collection and annotation of defective samples are expensive, resulting in abundant unlabeled data or limited labeled data. Therefore, researchers have begun investigating semi-supervised learning. In the semi-supervised mode, the training set contains both normal and abnormal samples, but only a small portion of samples have annotations. Compared to supervised learning, semi-supervised learning reduces the dependency on sample annotation, and compared to unsupervised learning, it can also utilize limited defective data.

Wang et al. [2] proposed noise-resistant semi-supervised learning by quantifying regional uncertainty. They studied the adverse effects of different forms of noise associated with pseudo-labels. Then, they quantified regional uncertainty by identifying noise-resistant characteristics of regions with different intensities, achieving better detection of industrial anomalies. Kun et al. proposed an active semi-supervised learning-based method for identifying surface defects in magnesium alloy laser welding. The proposed active semi-supervised learning method combines an Adaptive Dynamic Threshold Adjustment Module (ADTAM) and a Sample Selection Mechanism (SSM). It dynamically adjusts confidence thresholds and adaptively optimizes the pseudo-label generation process according to the characteristics of different defect categories. The method also incorporates regression loss from Region Proposal Networks and Regions of Interest, along with IoU (Intersection over Union) thresholds, to address class imbalance issues and improve pseudo-label quality.

The SSM analyzes consistency between teacher and student model predictions, filters high-quality pseudo-labels based on IoU, discards low-confidence labels, or incorporates them into the active sampling pipeline for annotation. Furthermore, after semi-supervised training, entropy-based active sampling is employed to identify the most informative unlabeled samples for manual annotation. Subsequently, these samples are added to the training set to further enhance the model's generalization.

However, if only a small amount of labeled data is used in supervised training, the model tends to overfit to the labeled samples and has difficulty generalizing to other unlabeled defects. To utilize unlabeled data, pseudo-labeling techniques are commonly employed. Compared to unsupervised learning, if a small amount of labeled defective samples can be provided, applying semi-supervised learning can significantly improve model performance. Kimura et al. [3] used a small amount of labeled defective samples under the semi-supervised learning framework to train an additional discriminator, enabling the network to generate better attention maps.

4.1. Methods based on pseudo-labels

Google's open-source semi-supervised anomaly detection framework uses ensemble one-class classifiers as pseudo-labelers for pseudo-label generation. It employs multiple one-class classifiers (such as Isolation Forest and One-Class SVM) to generate pseudo-labels for unlabeled data. The ensemble strategy fuses prediction results from multiple classifiers through voting or weighted averaging. Supervised fine-tuning uses real labels and high-confidence pseudo-labels to train deep networks. Pseudo-label methods augment the training set by generating labels for unlabeled data. Self-training uses high-confidence predictions as pseudo-labels in an iterative training process to gradually improve model performance. Co-training trains multiple complementary models that mutually provide pseudo-labels to each other.

4.2. Methods based on consistency regularization

The core idea is that for different perturbed versions of the same sample, the model should produce consistent prediction results. The model is trained by minimizing the prediction differences between different perturbed versions.

Mainly used to improve the model's generalization ability and robustness. The core idea is: for different perturbations or transformations of input data, the model's output should remain consistent or similar, thereby utilizing unlabeled data or augmented data to assist training.

Specifically, consistency regularization-based methods apply different perturbations to the same input during training (such as noise, data augmentation, random transformations, etc.) and force the model to produce consistent prediction results for these perturbed inputs. This constraint helps the model learn the underlying invariant features of inputs, reduces sensitivity to noise and irrelevant changes, and improves the model's stability and accuracy in practical applications.

In semi-supervised learning, consistency regularization is particularly important because it can effectively utilize large amounts of unlabeled data and improve model performance by maintaining prediction consistency on unlabeled samples.

5. Public datasets

5.1. Main datasets overview

Table 3. Commonly used public datasets for industrial defect detection

Names	Website	Introduction
NanoTWICE	http://www.mi.imati.cnr.it/ettore/NanoTWICE	45 images, non-periodic continuous textures, defects of varying sizes
MVTecAD	https://www.mvtec.com/company/research/datasets/mvtec-ad	15 categories, each with approximately 240 normal images and 100 defect images, with anomalous samples containing various defects
BTAD	http://avires.dimi.uniud.it/papers/btad/btad.zip	2830 images, including 3 types of industrial products, showcasing surface and structural defects
Fabricdataset	https://ytngan.wordpress.com/codes	3 types of fabric images, each with 25 defect-free and 25 defective images, 5 defect types
Textureddataset	https://www.mvtec.com/company/research/publications	2 types of woven fabric textures, all single-channel grayscale images
RSDDs	https://github.com/neu-rail-rsdds/rsdds	Collected on real railway tracks, including 113 two-dimensional color left images with corresponding depth images

MTDefect	https://github.com/abin24/Magnetic-tile-defect-datasets	1344 images, collected under various lighting conditions, containing 6 types of defects
AITEX	https://aistudio.baidu.com/datasetdetail/90062	245 images, 7 fabric structure categories, each category containing 20 defect-free samples
KolektorSDD	https://www.vicos.si/resources/kolektorsdd	Electronic commutator images, containing 348 defect-free images and 52 defective images
VTecLOCOAD	https://www.mvtec.com/company/research/datasets/mvtec-loco	5 categories, 2076 normal samples, 1568 abnormal samples,including structural anomalies and logical anomalies

Classification performance metrics are typically evaluated using accuracy, precision, and recall. Accuracy is defined as the proportion of correctly classified samples out of the total number of samples, and is suitable for scenarios with balanced samples. Precision and Recall: Precision is the proportion of true positives among predicted positives. Recall is the proportion of true positives among actual positives.

In addition, the F1 score, which is the harmonic mean of precision and recall, is also used for comprehensive evaluation. The calculation methods for the above metrics are shown as follows.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = TPR = \frac{TP}{TP + FN}$$

$$F1 - measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad (5.1)$$

In addition, models for industrial defect detection often use small classification datasets such as CIFAR-10 and MNIST, as well as video anomaly datasets such as STC, UCSD-Pred2, and CUHK Avenue for performance evaluation related to OOD tasks.

5.2. ROC curve and AUC

The ROC curve (Receiver Operating Characteristic Curve) is an important evaluation tool. This curve is plotted with False Positive Rate (FPR) as the horizontal axis and True Positive Rate (TPR) as the vertical axis, used to evaluate the overall performance of binary classification models.

AUC-ROC (Area Under the ROC Curve) is the area under the ROC curve, with a numerical range where AUC values fall between 0.5 and 1.0. A value of 1 indicates perfect classification ability, while 0.5 indicates no classification ability.

6. Conclusion

Semi-supervised learning and unsupervised learning have shown tremendous potential in the field of industrial defect anomaly detection, effectively addressing the problem of scarce labeled data. Through comprehensive analysis of existing methods, it can be seen that methods based on consistency regularization and pseudo-labeling perform exceptionally well in practical applications. Meanwhile, hybrid methods combining deep learning provide effective solutions for complex industrial scenarios.

Future research directions should focus on: (1) improving the robustness of methods to data distribution shifts; (2) enhancing model interpretability and trustworthiness; (3) developing lightweight models suitable for edge computing; (4) establishing more comprehensive evaluation systems and standardized processes. Through continuous technological innovation and industrial practice, semi-supervised learning and unsupervised learning will play increasingly important roles in the process of industrial intelligence.

Future development directions include multi-modal fusion, which integrates data from multiple sensors (such as visual, infrared, ultrasonic, etc.). In future developments, the accuracy and speed of defect detection may be significantly improved, making it suitable for more complex industrial environments.

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