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A Review on Recent Advances in Vision-based Defect Recognition towards Industrial Intelligence

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ABSTRACT

In modern manufacturing, vision-based defect recognition is an essential technology to guarantee product quality, and it plays an important role in industrial intelligence. With the developments of industrial big data, defect images can be captured by ubiquitous sensors. And, how to realize accuracy recognition has become a research hotspot. In the past several years, many vision-based defect recognition methods have been proposed, and some newly-emerged techniques, such as deep learning, have become increasingly popular and have addressed many challenging problems effectively. Hence, a comprehensive review is urgently needed, and it can promote the development and bring some insights in this area. This paper surveys the recent advances in vision-based defect recognition and presents a systematical review from a feature perspective. This review divides the recent methods into designed-feature based methods and learned-feature based methods, and summarizes the advantages, disadvantages and application scenarios. Furthermore, this paper also summarizes the performance metrics for vision-based defect recognition methods. And some challenges and development trends are also discussed.

1. Introduction

With the advances of industrial technologies, manufacturing is developing towards intelligence, automation and digitization [1]. This improvement not only increases production efficiency, but also brings a series of new challenges, and one of the biggest is product quality control. To guarantee product quality, full-inspection is a development trend in industrial intelligence, which can save unnecessary losses and improve product quality [4]. Recently, with the wide applications of sensors, the data collection of product quality has been addressed successfully [2,3]. This provides strong supports for the realization of full-inspection. However, full-inspection is still unachievable unless some challenges have been solved. And, one of the bottlenecks is how to recognize these defects accurately as well as effectively [5].

Traditionally, defects are usually recognized manually. But the efficiency is too low to satisfy the requirements of industrial intelligence. For example, in a steel workshop, the recognized area only covered about 0.05% of the total product [6]. Furthermore, the recognition results are also unstable because the inspectors are easy to fatigue.

With the development of computer vision, vision-based defect recognition has drawn increasing attention from both the industrial and academic. Vision-based defect recognition employs computer vision techniques to process defect images, and provides a fast, economical and stable manner for defect recognition. Therefore, it has been widely used in many fields, such as steel [7], wood [8], ceramic [9], fabric [10] and architecture [11].

Vision-based defect recognition is to identify if there are defects in the given images. As shown in Fig. 1, this process generally contains data pre-processing, feature extraction and recognition. Data pre-processing is to collect, clear and standardize the defect images. The recognition generally comprises classification, segmentation, detection and matching. Classification recognizes the defect types, segmentation distinguishes the defect and non-defect areas, detection shows the location of the defect, and matching is to find the most similar template. Feature extraction is an essential component in all these recognition tasks. A good feature extraction manner can enhance defect recognition performance. Traditionally, vision-based defect recognition methods can be categorized into statistical methods, structural methods, filter-based methods and model-based methods. In the past decades, several efforts of vision-based defect recognition have been reported. Chin [12] summarized the vision-based defect recognition methods in the 1980s, Newman and Jain [13] presented an overview in the 1990s. Xie [14] summarized advances in the 2000s. Li and Gu [15] reviewed the

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Nomenclature

AUC	Area under curve
CAE	Convolutional autoencoder
CNN	Convolutional neural network
DBNN	Deep belief neural networks
DL	Deep learning
FFT	Fast Fourier transform
FPGA	Field programmable gate array
GAN	Generative adversarial network
GLCM	Grey-level co-occurrence matrix
GNN	Graph neural network
GPU	Graphics processing unit
LBP	Local binary patterns
LCD	Liquid crystal display
LED	Light-emitting diode
LSTM	Long short-term memory
OLED	Organic light-emitting diode
PCA	Principal components analysis
RNN	Recurrent neural network
ROC	Receiver operating characteristic
TFT	Thin film transistor

techniques for the free-form surface. Neogi et al. [6] reviewed the defect recognition methods for steel surface. Kumar [16] and Ngan et al [4] proposed an overview of fabric defect recognition. However, many significant advances have been reported in artificial intelligence, and many newly-emerged techniques, such as deep learning [17,18], have been introduced into vision-based defect recognition. But there are few comprehensive reviews of these newly-developed methods. Therefore, this paper focuses on the recent advances in vision-based defect recognition, and presents a systematical review by expatiating the advantages, disadvantages and application scenarios.

As shown in Fig. 1, according to the different feature extraction manners, this review divides the recent advances into designed-feature based methods and learned-feature based methods. The designed-feature based methods are mainly based on traditional defect recognition methods, such as statistical methods, structural methods, filter-based methods, and model-based methods. The learned-feature based methods are mainly based on deep learning, and they are divided into convolutional neural network-based methods, autoencoder-based methods, and recurrent neural network-based method. This difference is because the feature extraction in deep learning is quite different from the traditional methods. In the traditional methods, features are extracted by the explicitly designed or selected operators. This relies on expert knowledge, and it is usually fast and lightweight, and the recognition results are also more explainable. While the learned-feature based methods can learn the feature automatically. It relies on less knowledge but requires a large dataset, and the training process is also

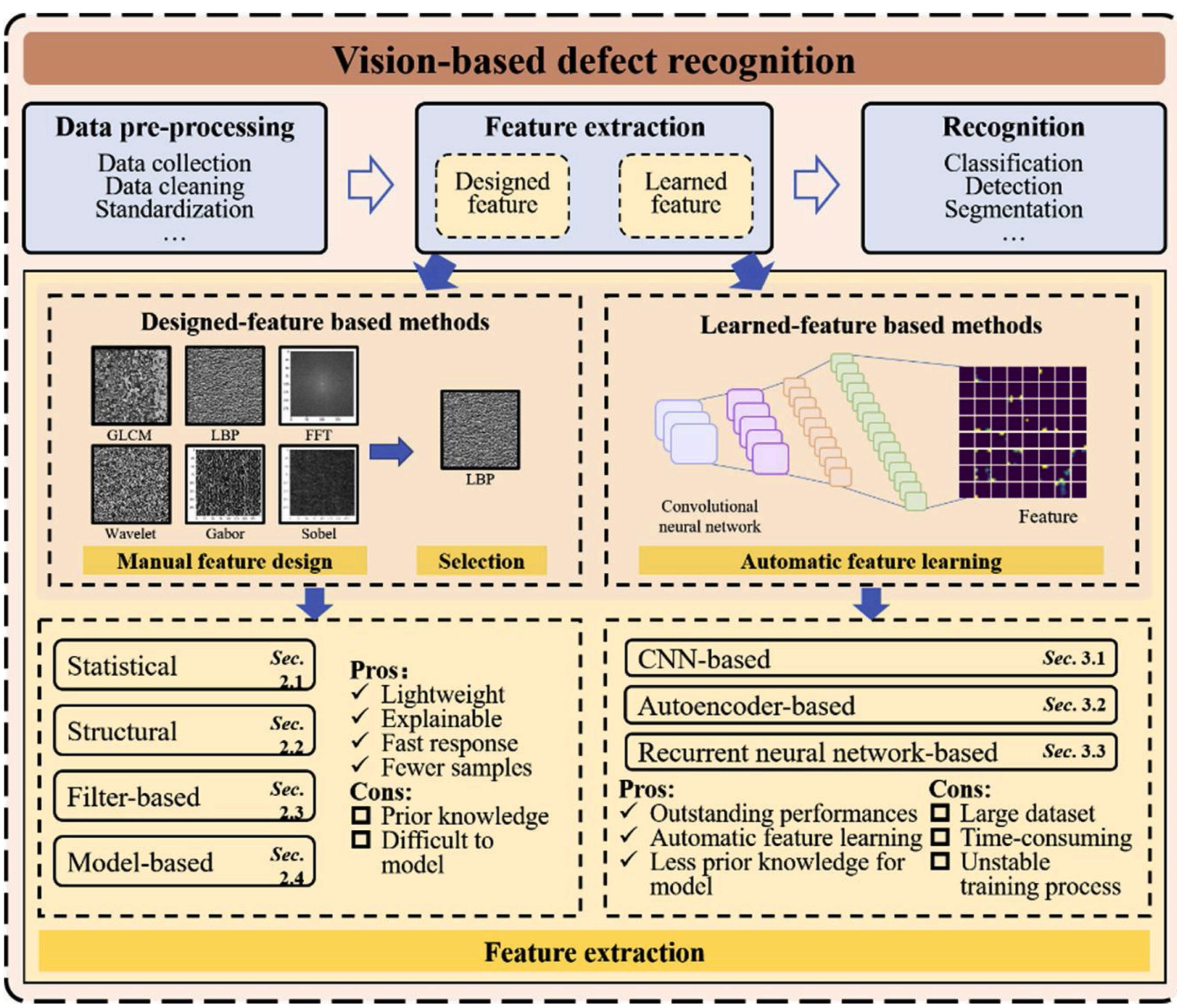

Fig. 1. The diagram of vision-based defect recognition.

time-consuming. The differences are also presented in Fig. 1. Besides the systematical review, this paper summarizes the performance metrics. Meanwhile, some research trends and challenges are also discussed.

The remainder of this paper is organized as follows. Section 2 reviews the designed-feature based defect recognition methods. Section 3 summarizes learned-feature based defect recognition methods. Section 4 presents some performance metrics for recognition results. Section 5 discusses some future research trends and challenges. Section 6 is the conclusion.

2. Designed-Feature Based Defect Recognition Methods

The designed-feature based methods use some explicit operators to extract features from defect images, and use simple classifiers for recognition. This extraction relies on expert knowledge, and it is more targeted to the tasks. As shown in Fig. 1, the designed-feature based methods generally contain statistical methods, structural methods, filter-based methods, and model-based methods. The list of these methods is summarized in Table 1, and more detail is discussed below.

2.1. Statistical Methods for Defect Recognition

Statistical methods extract statistical information from defect images, and analyze the spatial distribution of pixel values. As shown in Fig. 2, many statistical methods have been proposed for defect recognition, such as histogram information, co-occurrence matrices and local binary patterns (LBP).

Histogram information is a basic representation of images. Common histogram indicators include range, mean, geometric mean, harmonic mean, standard deviation, variance, and median. The comparison indicators involve L1-norm, L2-norm, earth mover's distance, Bhattacharyya distance, Matusita distance, divergence, histogram intersection. Lee et al. [20] developed a histogram-based defect recognition method, and used difference, mean, and standard deviation to analyze the defect images. Chen et al. [19] used 14 statistical features from the color spaces to handle the non-uniform illumination problem for bridge coating defect recognition. Chu et al. [22] proposed a multi-type statistical feature-based method for steel surface defect recognition. The features involve six one-dimensional histogram features, such as mean, variance, skewness, kurtosis, energy, and entropy, and five two-dimensional histogram features, including angular second moment, entropy, contrast, inverse difference moment and correlation. Manish et al. [21] used histogram information to understand the effect of surface finish on pixel intensity distribution. Ng [23] and Aminzadeh [24] proposed a thresholding method for defect recognition by histogram information. Histogram is easy to model and visualize, but the extracted information is limited.

Table 1
Summary of designed-feature based methods

	Methods	References and Scenarios
Statistical	Histogram	Bridge [19,20], grinding process [21], steel [22] and others [23,24]
	Co-occurrence matrix	TFT [25], wood [26], fabric [27,28], tyre [29], welding [30] aluminium [31]
	Local binary patterns	Welding [32], wood [33], fabric [34,35], steel [36], OLED [37]
	Others	TRISO [38], steel [39]
Structural	Morphology	Pipeline [40], fabric [41–43], wheel [44]
Filter-based	Spatial domain	Aluminium [31], rail [45,46], welding [47,48], tire [49], fabric [50]
	Frequency domain	Microscopy [51], fabric [52], semiconductor [53], solar cells [54], architecture [55], welding [56], other [57]
	Spatial-frequency domain	Rail [58], steel [59,60], wood [61] fabric [62–67], welding [68,69], tile [70], LCD [71], wafer [72], other [73]
Model-based	Markov random field, autoregression	Fabric [10], rail [74]

Co-occurrence matrices present the distribution of co-occurring pixel values at a given offset [75]. In defect recognition tasks, grey-level co-occurrence matrix (GLCM) is one of the common methods, and it has widely successful applications, such as TFT [25], wood [26], fabric [27,28] and tyre [29]. Chondronasios et al [31] introduced a gradient-only GLCM for aluminium profiles. Kumar et al. [30] proposed a GLCM-based method for welding. GLCM is more suitable for textured defects, which made a complete presentation of the spatial relation.

LBP was firstly proposed by Ojala et al. [76]. It calculates the grey value difference between all pixels in the neighbourhood pixels, and encodes all these calculated results into a binary pattern. Yan et al [32] proposed a completed local ternary patterns method for welding defect recognition, which improved the performance under different illuminations. Li et al. [33] proposed a local binary differential excitation pattern to extract the defect feature of wood. The local binary differential excitation pattern is generated by LBP and Weber's Lay. Song and Yan [36] proposed an adjacent evaluation completed local binary patterns for hot-rolled steel trip defect, and it eliminates the sensitive for noises. LBP usually works on grey-level images, Fekri-Ershad and Tajeriour [35] introduced a multi-resolution and noise-resistant LBP for color images, so that the color information can be used for defect recognition. Also, there are some variants of LBP for OLED [37] and fabric [34]. LBP can make a discriminative feature representation, but it might be sensitive to noise.

Besides these methods above, there are still some statistical methods that have been proposed in recent years, such as autocorrelation [38,39]. Statistical methods can give an intuitive and discriminative presentation of the defect, and they are easy to model, understand and visualize. But they usually have some assumptions, such as separable defect regions, which cannot satisfy all of the scenarios [14]. Furthermore, some of them are also sensitive to affine transformation and hyper-parameters.

2.2. Structural Methods for Defect Recognition

In structural methods, defect feature is characterized by texture elements. Therefore, the goals of the structural methods are to extract the texture elements of defects, and model the spatial placement rules by these elements [77]. In recent years, morphology [78] is the widely used method in structural methods. Su and Yang [40] used a morphological method to detect the leaking in sewer pipelines. Rebhi et al [41] proposed a fabric defect detection method, which used the local homogeneity to compute the morphology. Zhang et al. [44] used morphological reconstruction to detect the defect of aluminium alloy wheels. Jayashree and Subbaramn [42] proposed a hybrid method using correlation and morphology for plain weave fabric. Hu et al. [43] used morphological filters to detect the fabric defect, and it can reduce the influence of the uneven brightness distribution.

Structural methods are good at finding the geometry feature. This method is simple for computation, and more suitable for random textured defects. But most of them are sensitive to defect shape and size, and the defect images must be aperiodic.

2.3. Filter-based Methods for Defect Recognition

Filter-based methods apply some filter banks on defect images, and calculate the energy of the filter responses. As shown in Fig. 3, the common filter-based methods involve Sobel operator, Canny operator, Gabor operator, Laplacian operator, wavelet transform and Fourier transform, which can be further divided into spatial domain, frequency-domain methods, and spatial-frequency domain filter-based methods.

In the spatial domain, defect images are usually filtered by gradient filters, such as Sobel, Canny, Laplacian operators, to extract edges, lines, and isolated dots. Chondronasios et al. [31] used a Sobel edge detector

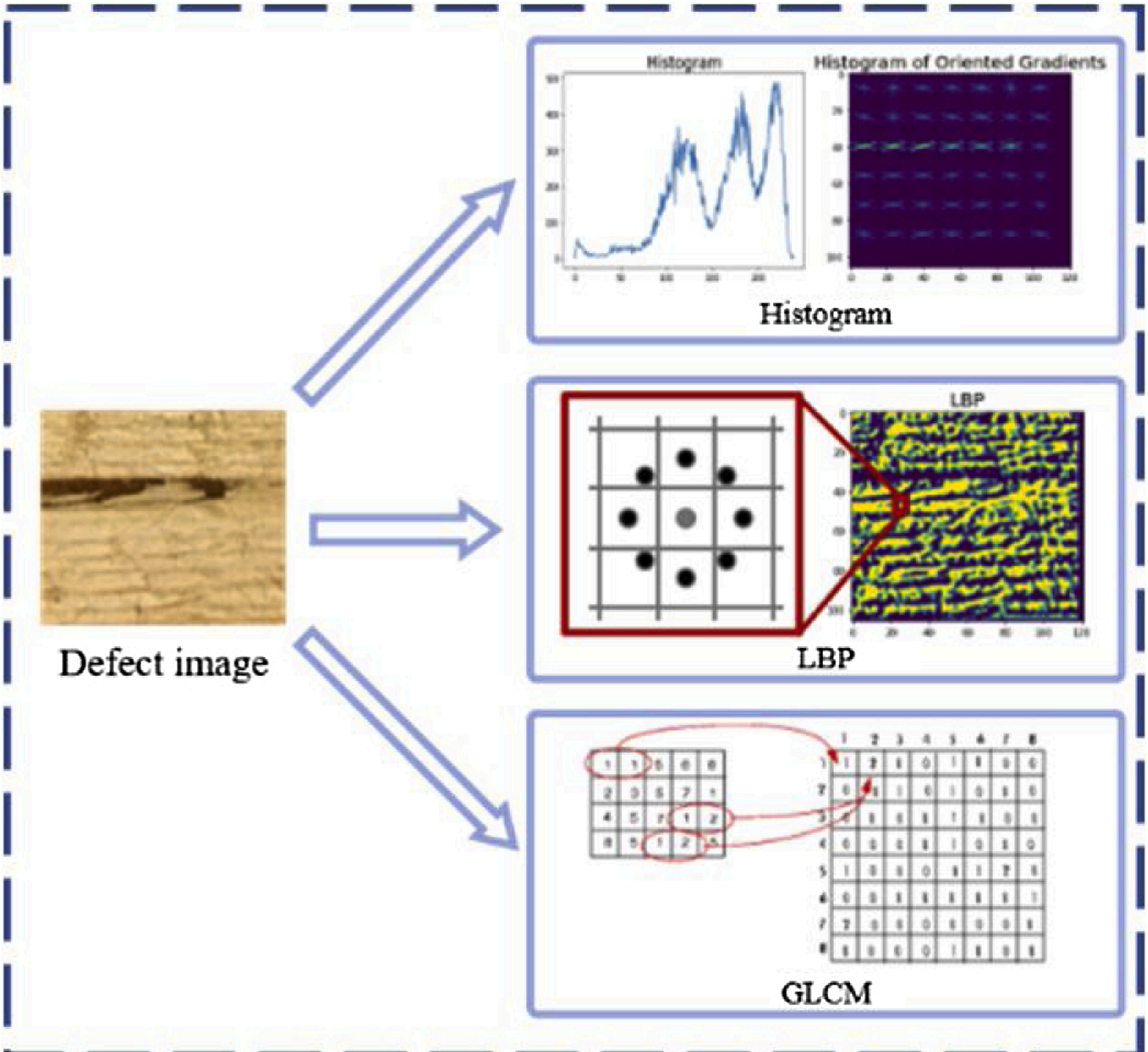

Fig. 2. Diagram of the statistical methods.

to obtain the gradient magnitude of the aluminium profiles. Based on the median filter, Ma et al. [79] introduced an improved Sobel algorithm, which overcomes the sensitive for noise. Shi et al. [45] also proposed an improved Sobel algorithm for rail surface defect recognition. Halim et al. [47] developed an automatic defect inspection system, and used a Sobel-contour method for welding defect. Zhang et al. [49] used a Canny operator for the tire. Hou and Liu [48] used a Canny operator for welding image edge detection and identification. Manish et al. [21] used a Canny operator to describe the edge defect in a grinding process. Ma et al. [50] proposed an adaptive Canny operator for fabric defect detection. Tastimur et al. [46] used a Laplacian low-pass filter for rail defect recognition.

The spatial domain-based methods are usually noise-sensitive, while the frequency domain filter-based methods can address this problem well. Fourier transform is one of the common methods to transform the defect images into the frequency domain. Ajithaprasad et al. [51] used Fourier spectrum analysis method to detect the defect in diffraction phase microscopy. Kumaresan [52] used a Fourier analysis method for texture defect. Bai et al. [53] proposed a phase-only Fourier transform-based method, and it is effective to identify the defect and non-defect area. Pastor-Lopez [57] proposed a defect modeling method that combined a co-occurrence matrix with fast Fourier transform, which was successfully applied on several defect recognition tasks. Tsai et al. [54] used Fourier reconstruction for solar cells defect recognition. Chen et al. [55] proposed a Fourier transform-based method for automated steel bridge coating defect recognition. Timm et al. [56] used statistical Fourier descriptors for welding defects.

Fourier transform might not be suitable for the local defect, because the Fourier coefficients are calculated by global information. This drawback is usually addressed by the methods in spatial-frequency domain, such as Gabor filter and wavelet transform.

Gabor filter introduced a Gaussian window function into Fourier transform. Vijaykumar and Sangamithirai [58] used Gabor filters for rail defect recognition. Tikhe and Chitode [59] used Gabor filters for steel surface defect recognition. Tolba et al. [60] proposed a defect recognition method with a log-Gabor filter. Tong et al. [63] used differential evolution to find the optimal Gabor filter, and applied it to fabric defect recognition. Hu [73] and Jing et al. [65] used genetic algorithm to optimize the Gabor filter. Bissi et al. [64] combined Gabor filters and PCA to detect the defect in uniform and structured fabrics.

Wavelet transform is also widely used, which optimizes the frequency-dependent temporary resolutions. In wavelet transform, defect images are considered as a weighted sum of overlapping wavelet functions. Li and Tsai [72] proposed a wavelet-based defect recognition

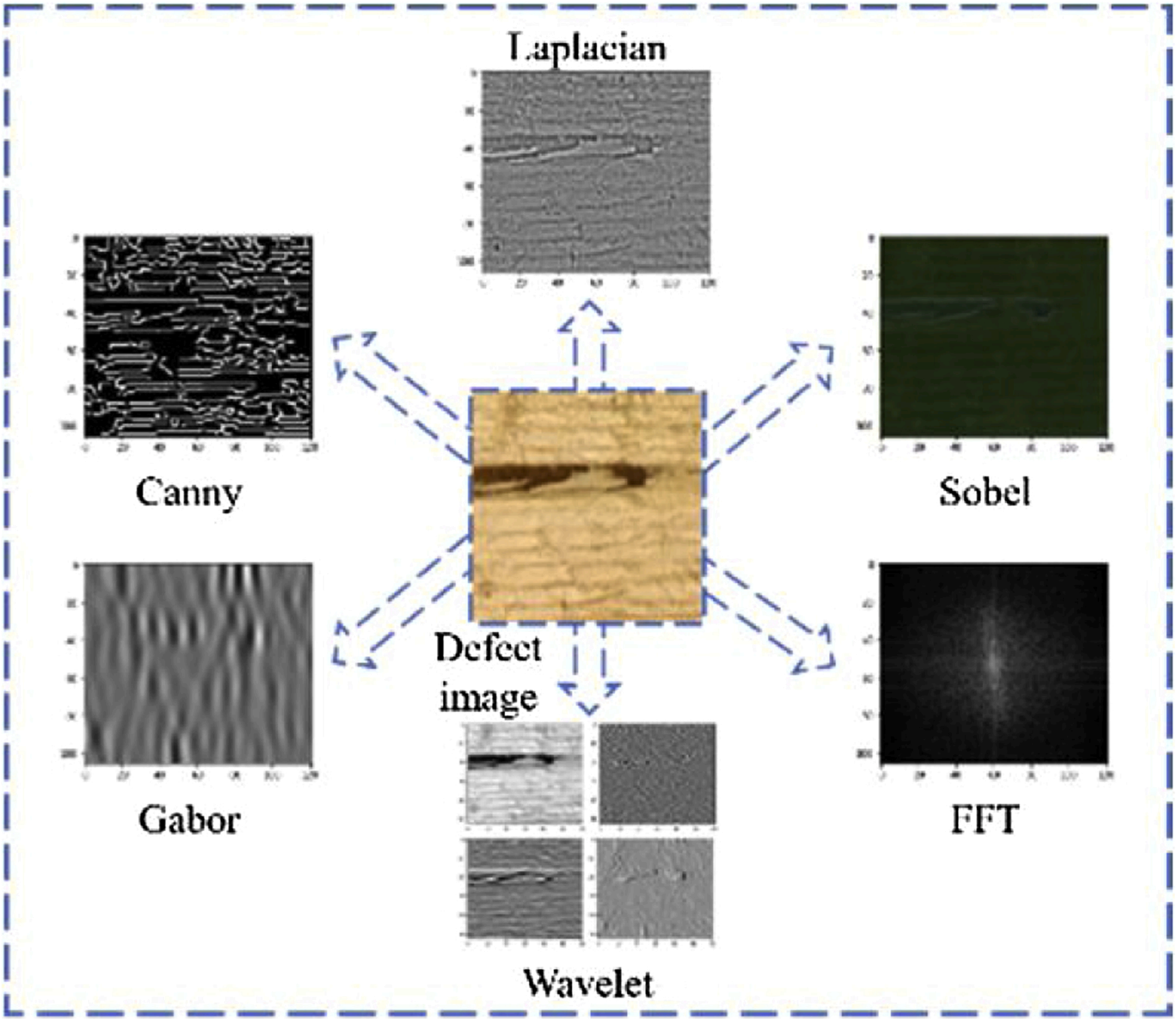

Fig. 3. Diagram of filter-based methods.

method for the solar wafer. Li et al. [66] used a multi-scale wavelet transform for fabric defect recognition. Kang et al. [67] developed a fabric defect detection method based on wavelet transform. Liu et al. [68] used wavelet packet transform for spot welding. Yang et al. [61] proposed multi-scale edge detection for the wood defect with dyadic wavelet transform. Bi and Sun [62] used undecimated wavelet transform to detect fabric defect. Yang et al. [70] used stationary wavelet transform for magnetic tile defect. Das et al. [69] combined wavelet transform and Hilbert-Huang transform for welding defect recognition. Wang et al. [71] combined singular value decomposition and wavelet transform to defect LCD defect.

The filter-based methods are common in vision-based defect recognition. The joint domains can help the model to extract more useful information. Moreover, they are invariance to affine transformation, and can handle multi-scale defect images. However, filter-based methods might be not suitable for random textured images, and some of them might be affected by feature correlations and noises.

2.4. Model-based Methods for Defect Recognition

In the defect recognition tasks, such as fabric, the defects are often mixed with stochastic and deterministic components. The defect images can be observed as the realizations or the samples from parametric probability distributions on the image space [80]. This defect detection problem can be treated as a statistical hypothesis-testing problem on the statistics derived from this model. Model-based defect recognition methods are particularly suitable for defect images with stochastic variations. Cao et al. [10] proposed a knowledge-guided autoregressive method for fabric defect. Myklebust [81] proposed zero-defect manufacturing with Markov random fields. Jin et al. [74] combined Markov random fields and deep learning for rail defect inspection.

Model-based methods usually combine with the other methods, such as statistical method, and they are more suitable for stochastic variations. But model-based methods might be difficult to model, and they might not work well on small defects.

2.5. Brief Summary

Table 2 gives a summary of the designed-feature based methods, and analyzes the strengths and weakness of these methods. The biggest advantage of these designed-feature based methods is that they are more targeted to the defect images. This advantage helps the designed-feature based methods to extract more useful feature from fewer samples. Meanwhile, some designed operators [35,36,79] also show the robustness to noisy images. Furthermore, since the explicit design, these methods are usually lightweight and interpretable. These can provide a fast response time for recognition and a creditable result for analysis. The limitation of the designed-feature based method is that the explicit design requires expert knowledge, which will lead to a poor result if the operator is not appropriate. Thus, these methods are more difficult to

Table 2
Strengths and weakness of the designed-feature based methods

Methods	Strengths	Weakness
Statistical	• Easy to model, understand and visualize • Robust to noise • Discriminative feature space • Low computation	• Requires some assumptions, such as separable defect regions • Sensitive to affine transformation • Manual parameter selection or operator design
Structural	• Simple computation • Suitable for random textured defects	• Defect images must be aperiodic • Sensitive to defect shape and size
Filter-based	• Invariance to affine transformation • Can handle multi-scale defect images • Joint domains can extract more useful information	• Not suitable for random textured defect images • Sensitive to noise • A little complex, and difficult to find the optimal parameter • Might be affected by correlations
Model-based	• Easy to combine with the other methods, such as the statistical • Suitable for the defect images with stochastic variations	• Difficult to model • Cannot detect small defects

model. Furthermore, some methods require some assumptions, such as separable and aperiodic.

3. Learned-Feature Based Defect Recognition Methods

The learned-feature based defect recognition methods can extract features and useful information automatically, which avoids the explicit feature design. This advantage makes the learned-feature based defect recognition require less prior or expert knowledge. In the past decade, most of the learned-feature based defect recognition methods are based on deep learning (DL) [82]. Thus, this section will mainly summary these DL methods., which are categorized according to the different model architectures, including convolutional neural network (CNN), autoencoder, and recurrent neural network (RNN). Autoencoders uses encoders and decoders, CNN uses convolutional layers, and RNN uses recurrent connections. These methods are summarized in Table 3, and more detail is discussed below.

3.1. CNN-based Defect Recognition Methods

Convolutional neural network (CNN) was firstly proposed by LeCun et al. [141], which is composed of convolutional layers, pooling layers and classification layers. The diagram of CNN is presented in Fig. 4. Furthermore, some technologies are also used to improve the performance, such as dropout [142] and batch normalization [143]. CNN and its variants have achieved state-of-the-art performance for image recognition [17,144]. Thus, CNNs have drawn more and more attention [117,145].

Park et al. [83] tested several CNN networks, and suggested that a single CNN network has a strong ability to identify the defect and non-defect. Masci et al. [87] proposed a max-pooling CNN to recognize steel defects. Khumaidi et al. [93] proposed a CNN with Gaussian kernels for welding defect. Zhang et al. [91], Miao et al. [95] and Zhu et al. [92] also used CNN for welding defect. Zhang et al. [119] used a one-class CNN to detect the abnormal defect in the electronic component. Zhong et al. [100] proposed an improved CNN, and used Hough transform and Chan-Vese model to detect the catenary split pins in a high-speed railway. Xu et al. [101] and Liu et al. [108] used a region-based CNN to detect the defect in railway subgrade and fabric. Nakazawa and Kulkarni [103] and Cheon et al. [102] used CNN for wafer defect. Wang et al. [120] developed a robust CNN for noisy images. Lin et al. [107] proposed a deep CNN to detect the defect in LED, and used class activation mapping technology to localize the defect regions. Kim et al. [105] proposed an ensemble CNNs for TFT-LCD panel. Tao et al. [96] proposed a multi-task CNN for wire defect. Lu et al. [115] proposed a visual transformation CNN to estimate the defect size. Chen et al. [109] designed a multi-spectral CNN, and developed it into solar cell surface defect recognition. Iwahori et al. [97] used CNN to recognize the defect of electronic boards. Xu et al. [110] proposed a small data driven-CNN for subtle roller defect recognition. He et al. [84] proposed a CNN-based method for steel surface defect recognition with fusing multiple hierarchical features. Chen et al. [85] proposed an ensemble CNNs that combined different CNNs, including residual networks and wide residual networks, to improve the recognition accuracy for steel surface defect. Gao et al. [5] proposed a semi-supervised CNN method, and developed it into steel surface defect recognition. He et al. [89] proposed a generative adversarial network-based semi-supervised defect recognition method with multi-training. Tabernik et al. [116] proposed a CNN-based surface defect segmentation method for surface-crack detection. Krummenacher et al. [111] used CNN to extract a discriminative feature for wheels. Song et al. [98] and Faghih-Roohi et al. [99] also proposed a CNN-based method for rail surface defect detection. Wang et al. [118] combined CNN with Hough transform to identify the defective and defect-free bottles. Furthermore, CNN was also widely used in the area of additive manufacturing [112], Wang et al. [114] used CNN to build a surface monitoring system for fused deposition modeling. Minnema et al. [113] used CNN for medical additive manufacturing.

Besides the outstanding performance, lots of available pretrained models is another advantage of CNN. Previous work [146] has proven that these pretrained models can provide a prior initialization of the parameters. With the pretrained parameters, the models can make a better feature representation and extraction, and converge fast. The conventional pretrained models involve VGG16 and VGG19 [17], residual network [144], and Decaf [146]. In the previous, Ren et al. [86] used a pretrained Decaf for defect recognition tasks, including classification and segmentation. Gao et al. [88] proposed Gaussian-pyramid based method for defect recognition, and used the VGG16 network as the basic model. Yang et al. [106] used a transfer learning CNN for LED. Yang et al. [94] used a pretrained VGG network to identify welding defects.

Besides these advantages, CNN is also robust for affine transformation, and several advances, such as generative adversarial net [90], have combined with CNNs. However, CNN usually requires a large dataset, and is time-consuming for model training. Noise-sensitive might be another weakness, but many improvements have been introduced to solve this problem.

Table 3
Summary of learned-feature based methods

Methods	References and Scenarios
CNN-based	Steel [5,83–90], welding [91–95], electronic component [96, 97], rail [98–101], wafer [102–104], LED [105–107], fabric [108], solar cell [109], roller [110], wood [86], wheel [111], additive manufacturing [112–114], other [115–121]
Autoencoder-based	Rail [122,123], steel [124–126], fabric [127–130], screen [131–133], wafer [134], other [135,136]
RNN-based	Aircraft [137], welding [138], steel [139], TFT [140]

3.2. Autoencoder-based Defect Recognition Methods

Autoencoder is an important DL model, which composed of encoder and decoder, and it provides a layer-wise pretraining to overcome the gradient vanishment in a deep architecture. In recent research, autoencoder and its variants, such as deep belief neural networks (DBNN) [18], denoising autoencoder and convolutional autoencoder (CAE), are widely used for defect recognition. The diagram of autoencoder is shown in Fig. 5.

Kang et al. [122] used a denoising autoencoder for high-speed

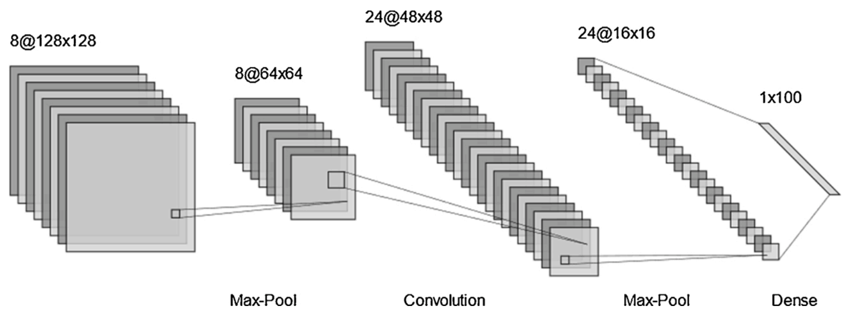

Fig. 4. The diagram of CNN architecture [141].

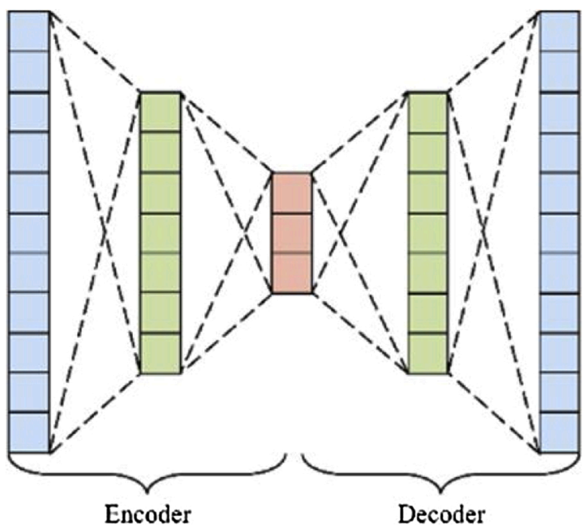

Fig. 5. The diagram of autoencoder.

railway insulator defect detection. Wei and Ni [123] also proposed an autoencoder-based method for rail defect identification. Kholief et al. [124] and Youkachen [126] used autoencoders for steel surface defect recognition. Yang et al. [128] developed a multiscale clustering-based fully convolutional autoencoder to identify the defect and non-defect. An adversarial autoencoder-based defect recognition method is proposed by Nakatsuka et al. [136]. Tian and Li [129] proposed an autoencoder-based method with cross-patch similarity for fabric. Mei et al [130] developed an autoencoder method, which uses a Gaussian pyramid for information fusion, and developed it into several defect recognition tasks. Ke et al. [131] used a convolutional autoencoder to detect the anomaly logo in mobile phone. Ku [133], Jo and Kim [132] used a concentrated autoencoder and a regularized autoencoder for display panel defect inspection. Mujeeb et al. [125] proposed a one-class autoencoder for defect detection. Yu [134] proposed a stacked denoising autoencoder to recognize the wafer map defect. Li et al. [127] proposed a Fisher criterion-based stacked denoising autoencoders for fabric defect. Feng et al. [135] used a deep belief neural network to detect the defect of material.

Pretraining is one of the characters of autoencoder. This makes autoencoders suitable for segmentation tasks, and it can work both with or without sample labels. However, this pretraining also prevents the model to build a deeper architecture. Meanwhile, it is time-consuming for model training.

3.3. RNN-based Defect Recognition Methods

Recurrent neural network (RNN) is a famous DL architecture to process time series. RNN uses a recurrent architecture to memorize the information, and the diagram of RNN is shown in Fig. 6. Generally, RNN and its variants, such as long short-term memory (LSTM), are widely used in natural language processing [147,148], and it is better to process series and text, but not to images. Thus, they are seldom used in defect recognition tasks.

Hu et al. [137] used an LSTM to recognize the aircraft defect with infrared thermography. Liu et al. [138] combined CNN and LSTM to recognize the welding defect. This method used a shallow CNN model to extract the primary feature, and used LSTM for feature fusion. Liu et al. [139] also proposed a steel surface defect recognition method based on CNN and LSTM, whose experimental results indicate that this hybrid method is better than the individual CNN or LSTM. Abeysundara et al. [149] proposed an RNN-based method for TFT line defect recognition, and used a multi-objective evaluation algorithm to optimize the topology architecture. Lin et al. [140] proposed a recurrent fuzzy cellular neural network for a real-world LCD defect inspection.

RNN is more suitable for time series. Thus, it usually combines with convolutional blocks for vision-based defect recognition. The recurrence can promote the feature reuse, and make a deep architecture with fewer parameters. But they are more difficult and complex to model and train. Meanwhile, it also a little slow for response.

3.4. Brief Summary

Table 4 gives a summary of the learned-feature based methods, and analyzes the strengths and weakness of these methods. Learned-feature based methods can learn the feature automatically, which avoids the explicit design of the feature extractor. In the learned-based methods, CNN is the widely-used model, and most of the recent work is based on CNN or its variants. Compared with the other models, CNN can retain spatial information from both the global and the local. Autoencoder is

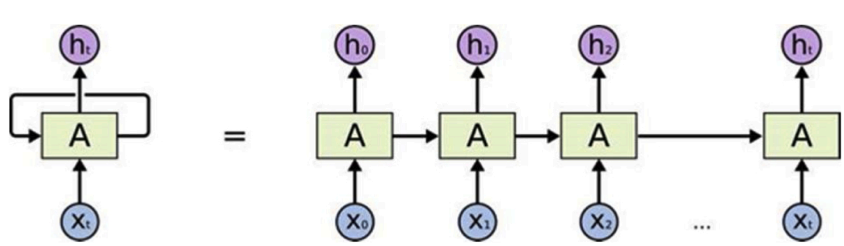

Fig. 6. The diagram of RNN architecture.

Table 4
Strengths and weakness of the learned-feature based methods

Methods	Strengths	Weakness
CNN	• Outstanding performance on classification and object detection • Pretrained models, such as VGG16, provide a better initialization • Robust to affine transformation	• Require a large dataset for training • Sensitive to noise • Time-consuming for training and applying • Require sample labels
Autoencoder	• More suitable for segmentation • Can work both with or without sample labels • Can be used to denoise • Fewer trainable parameters	• Cannot build a deep architecture, which caused by pretraining • Not good at classification and detection • Time-consuming
RNN	• Usually with convolutional block • Feature reuse by recurrence • Deeper architecture with fewer parameters (unrolling)	• Time-consuming for training and applying, due to recurrence • Complexity for model and training

usually used for segmentation tasks by reconstruction, and the previous work [150] suggests that using the convolutional network architecture in autoencoder can provide better performance.

The biggest advantages of learned-feature based methods are the outstanding performance and the ability of automatic feature extraction. However, as a newly-emerged technique, learned-feature based methods still have some drawbacks. Firstly, DL usually requires lots of samples for model training, but collecting and labelling samples are time-consuming and costly. Secondly, most of these methods have large network architectures, which are not conducive for the fast response. Thirdly, the training process is unstable, DL models might collapse with an inappropriate training manner. Finally, since DL methods learn the feature directly from the defect images, the defect images must be high-quality. Furthermore, the recognition results are usually poorly interpretable, and this is not conducive for the defect analysis.

4. Performance Metrics for Defect Recognition

The performance metrics evaluate the performance of a defect recognition method. In this paper, the performance metrics are summarized from aspects of accuracy and time.

4.1. Accuracy Indicators

Accuracy indicators evaluate the accuracy of the recognition methods. These indicators are very important for model design and selection. Actually, for a defect recognition task, the defect samples are usually divided into the training set and testing set. The training set is used for model training, and all the evaluations are based on the testing set. If a method performs well on the accuracy indicators, this method is feasible for the current task. On the contrary, poor performance will cause misclassification and unnecessary loss. The common indicators involve Accuracy, Recall, Precision, and F1-score. The definitions of these indicators are defined as follows.

$$
\begin{aligned}
Accuracy &= \frac{TP+TN}{TP+TN+FP+FN} \\
Recall &= \frac{TP}{TP+FN} \\
Precision &= \frac{TP}{TP+FP} \\
F1-score &= \frac{2*Precision*Recall}{Precision+Recall}
\end{aligned}
\tag{1}
$$

where TP and TN are the numbers of true positive and true negative samples, and FP and FN denote the false positive and false negative samples. Recall measures the ability to find the positive samples, while Precision measures the ability that the method does not misclassify a positive sample. Accuracy is the comprehensive performance of the method, and F1-score can be interpreted as a weighted average of precision and recall. For each indicator, the best value is 1 and the worst is 0. For conventional recognition tasks, Accuracy is enough to evaluate the performance. While if the dataset is imbalanced, the other three indicators will be necessary.

Besides these indicators, receiver operating characteristic (ROC) and area under curve (AUC) are also widely used to evaluate the performance of defect recognition methods. ROC is used to evaluate the performance of a classifier, whose discrimination threshold is varied. The AUC value is equivalent to the probability that a randomly chosen positive example is ranked higher than a randomly chosen negative example [151].

4.2. Time Indicators

Time indicators are very important for the application of the recognition methods, which reflect how fast the model can respond to the defect samples. In some real-world scenarios, such as steel, the production speed is fast, and it has a strict requirement for response time. Although a defect recognition method performs outstandingly on accuracy indicators, the slow response speed will also prevent its applications. This indicator should be of particular concern in the learned-feature based methods, which perform large network architectures.

The time indicators should include the training time, loading time and response time. The training time reflects how long before it can get a well-trained model. Loading time means how long the well-trained model can be loaded into the defect inspection system. Response time is how fast the method can handle the defect samples. The response time gives the upper limit of the recognition speed, and shows how fast production speed this method can satisfy. Moreover, it should be noticed that different hardware has different performance on the time indicators, thus, application environments should be mentioned while evaluating the time indicators. This can also provide a guideline to the one who wants to establish a defect inspection system.

4.3. Common Datasets for Vision-based Defect Recognition

Data is important for vision-based defect recognition methods. The designed-feature based methods need to observe the defect data and design operators to extract useful feature. The learned-feature based methods need to learn some useful information from the defect images. If someone wants to propose a generic method, the common datasets can also be used as benchmarks and provide a fair comparison with the other methods. Moreover, the common datasets can help beginners to know this field quickly. Thus, a summary of the common datasets is necessary. This paper summarizes the common datasets available in the reported work.

Song and Yan [36] proposed a hot-rolled steel strip dataset, called Northeastern University Dataset (NEU). This dataset involves six defect type, including crazing (Cr), inclusion (In), patches (Pa), pitted surface (PS), rolled-in scale (RS) and scratches (Sc), each of which contains 300 samples. The examples of the NEU dataset are presented in Fig. 7 a). Furthermore, the NEU dataset has a detection version (called NEU-DET) [84], which annotates the location of a defect in each image. Silvén et al. [8] proposed a wood dataset with several defect types, including core stripe, knot, mould, resin, resin pocked, split and wane. This dataset can be used to evaluate the methods of detection and classification. The examples of this dataset are shown in Fig. 7 b). In literature [116], Kolektor Group built a surface defect dataset (KolektorSDD). This dataset is proposed for surface defect segmentation, and microscopic fractions or cracks were observed on the surface of the plastic

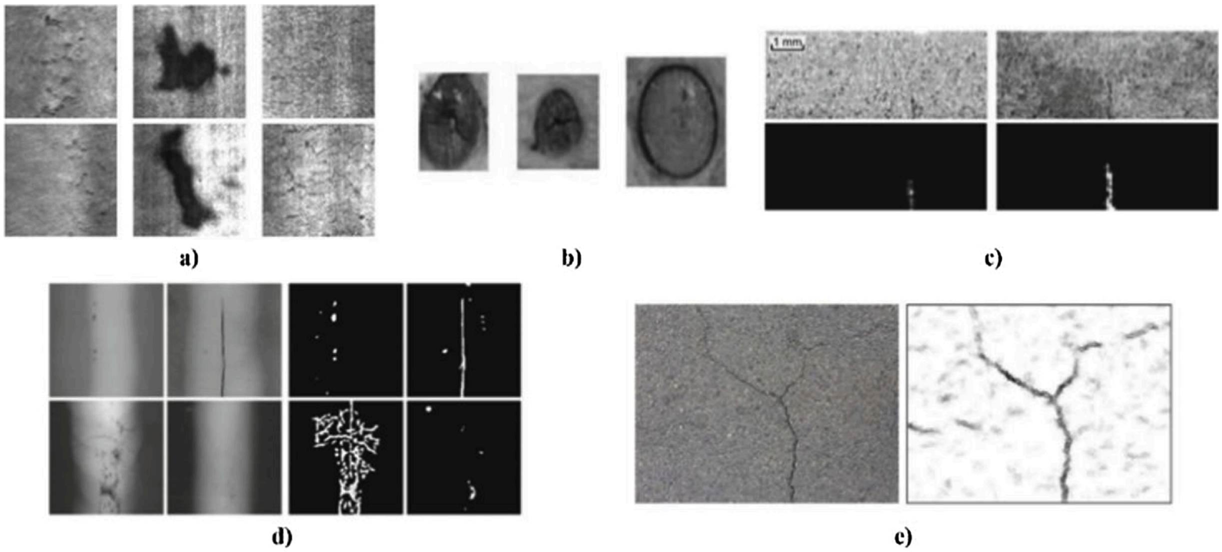

Fig. 7. The examples in different defect dataset.

embedding in electrical commutators. The examples of KolektorSDD are presented in Fig. 7 c). Mery et al. [152] presented a public dataset called GDXray. This dataset consists of 19,407 X-ray images with five groups, including casing, welds, baggage, natural objects and settings. Each group has several series, and each series several X-ray images. Most of the series are annotated or labelled. The examples of GDXray are shown in Fig. 7 d). Furthermore, Shi et al. [153] proposed an annotated road crack image dataset, which can reflect the urban road surface condition in general. The examples are shown in Fig. 7 e). All these datasets are summarized in Table 5.

Table 5
Summary of the public defect recognition datasets

Name	Tasks	Description	Scenario
NEU dataset	Classification	300 samples each of six different kinds of typical surface defects	Hot-rolled steel strip
NEU-DET	Detection	300 samples each of six different kinds of typical surface defects. Careful annotations of the defect location.	Hot-rolled steel strip
Wood dataset	Classification/ detection	A database of knot images for defect classification, and some manually classified region-by-region images for detection	Spruce wood
KolektorSDD	Segmentation	Microscopic fractions or cracks on the surface of the plastic embedding in electrical commutators. 300 images, involving 52 images of visible defect and 347 images without any defect	Electrical commutators
GDXray	Segmentation	88 images arranged in 3 series taken by the BAM Federal Institute for Materials Research and Testing	Welding
Road crack	Segmentation	An annotated road crack image dataset which can generally reflect the urban road surface condition in China	Transportation

5. Challenges and Trends in Vision-based Defect Recognition

The goal of vision-based defect recognition is to fuse human knowledge into the model, and to provide a fast and end-to-end manner to recognize the defect type with little human intervention. More importantly, defect recognition should provide some evidence to help production control. However, as shown in Fig. 8, many challenges must be solved before achieving these goals. This section will discuss the challenges and development trends in vision-based defect recognition. The discussion is based on data perspective, model perspective and application perspective.

5.1. Data Perspective

Most of the vision-based defect recognition is data-driven, so data is essential for a recognition method. However, building a defect dataset has several challenges.

1) Low-value. Some defects occur with low probabilities, which might cost a long period to collect enough defect images. This limitation is more prominently in the learned-feature based methods, which require a large dataset for model training.
2) Manual pre-processing. The production environment is intricacy, and the collected defect images might be complex. Thus, it requires explicit repair to process and select these images. Otherwise, it will influence the performance of the recognition methods.
3) Requirements for sample labels and annotations. Most of these methods require labels and annotations. But these processes are time-consuming, costly, and highly-expert-knowledge depended, especially for detection tasks, which is pixel-level annotation.

Although collecting samples is difficult, there is still another way to get enough samples. For example, using GAN [154] (generative adversarial network) or other data augmentation methods to generate some fake and vivid samples. But diversity should be considered. Otherwise, the fake samples will be useless. Moreover, some new technologies, such as digital twin [155–159], will also be useful for data collection. End-to-end processing is another trend for vision-based defect recognition, and how to develop human knowledge into an automatic model to replace human repair will be a key point for this problem. Using GAN to learn the defect information and reconstruct the low-quality defect images might be a good solution [90], and the other manners, such as autoencoder, might also be feasible. Labeling samples is an essential

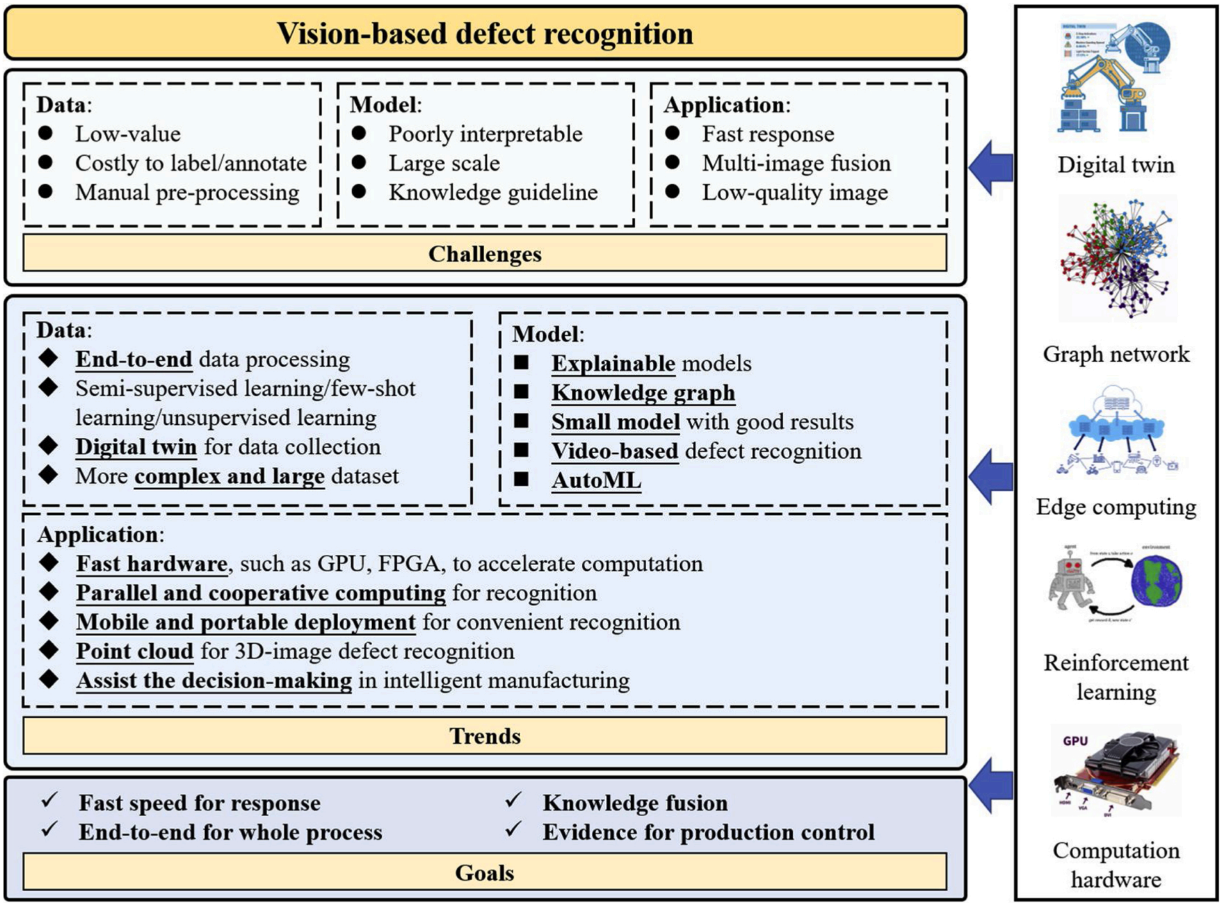

Fig. 8. Challenges and trends in vision-based defect recognition.

process, since most of the recognition methods are supervised learning. Thus, how to extract more useful information from the unlabeled samples is a compromise development trend. Semi-supervised and unsupervised learning can provide a feasible solution, and unsupervised learning is the ultimate goal for end-to-end automatic defect recognition, which does not need the sample label.

5.2. Model Perspective

In this paper, defect recognition methods are divided into designed feature-based and learned-feature based methods, and learned-feature based methods have drawn more and more attention with outstanding performance. However, learned-feature based methods also have many challenges.

1) Lack of knowledge guideline. Learned-based methods can extract feature automatically, so that the expert knowledge is always ignored. This is not conducive for model training, because it will be harder for the model to find the optimal solution without prior knowledge.
2) Poor interpretability. Automatic feature extraction is a black box with poor interpretability. Thus, the recognition results are not convincing if they cannot tell the judgement criterion.
3) Large scale. Learned-feature based methods, which perform DL models, are usually large scale. This might cause the recognition model slower to response and harder to deploy, and it might lead to a higher requirement for the hardware.

Introducing expert knowledge into learned-feature based methods can provide prior knowledge for the model. This can initialize better parameters, extract more targeted feature, and make the training more stable. Using a knowledge graph to fuse the expert knowledge and guiding the model training will be a valuable trend. Furthermore, the targeted feature will also make the recognition results more interpretable. Besides knowledge, inference is another way to improve interpretability. Graph neural network (GNN) is one of the newly-emerged technologies, which has a strong ability for inference. Using GNN to infer the defect is a new research hotspot. This will make the recognition results more explainable. Model compression is another trend for the recognition model, and the compression technologies, such as knowledge distillation and teacher-student model, is worth studying. On the one hand, the small model will make a fast response. On the other hand, it is also convenient for deploying into mobile terminals. The existed methods are focus on image-level, while video will present more useful information, and it can satisfy faster production speed. But this field is under-developing. To achieve the goal of end-to-end defect recognition, the recognition model also needs to have the ability of self-learning. A model must find the optimal architecture or parameters by itself. And some new technologies, such as reinforcement learning [160] and AutoML [161,162], will be useful to help this process.

5.3. Application Perspective

Application and deployment are the final goals of the defect recognition methods. But for most of these methods, there are still some challenges before applying them to a real-world case, even they have already achieved outstanding performance on the public datasets.

1) Computation time. Computation time is one of the biggest limitations for applications. Some of the recognition models are too large

and slow for real-time defect recognition, which will influence production.
2) Low-quality image. The real-world production environment is more complex, so that the collected defect images might not be as good as the public dataset. And this will influence the recognition performance greatly.
3) Single source. Most of the methods can only process the data from a single source. But in some scenarios, using the data from multi-sources will provide more useful information, and better recognition results.

As analyzed above, model compression is a good manner, and the new computation hardware, such as GPU and FPGA, and computation frameworks, such as parallel computation and edge computing [163], will also be helpful. Furthermore, these new computation manners can also help the deployment in mobile terminals, which is convenient for the inspectors. 3D defect recognition is another trend. Compared with 2D-image, 3D-image contains more information. For a product with complex surfaces, 3D technologies, such as cloud point, will be better. But this trend also has many limitations. Firstly, the equipment is expensive. Secondly, the recognition speed is slow. Finally, how to handle these 3D images is still under-developing. Repairing or reconstruction might be a good solution for the low-quality defect images, and some new technologies, such as GAN, also show effectiveness in this field [90]. Further, only giving the defect types are not good enough. A good recognition method should be connected with the process parameters, and once a defect occurred, it can also give some suggestion for production control.

6. Conclusion

Vision-based defect recognition is an essential technology to guarantee product quality, and plays an important role in industrial intelligence. Since many advanced techniques, such as deep learning, have been introduced into vision-based defect recognition, a comprehensive review is urgently needed to summarize and promote the development in this field. This paper divided the recent advances in vision-based defect recognition into designed-feature based methods and learned-feature based methods, and presents a systematical review from a feature perspective. From this review, most of the outstanding methods are based on learned-feature based methods, which perform feature extraction in an end-to-end way. But these methods still have many problems to be solved before been widely used. The designed-feature based methods rely on human knowledge, while learned-feature based methods rely on data. For the realization of industrial intelligence, the recognition models need to be fast, lightweight and accurate, and it can be hard realized by neither designed-feature based methods nor learned-feature based methods individually. Therefore, how to fuse the useful prior knowledge into deep learning models, and use both data and knowledge completely is a valuable research trend.

Declaration of Competing Interest

The authors report no declarations of interest.

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