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SURVEY

A Survey of Defect Detection Applications Based on Generative Adversarial Networks

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ABSTRACT With the development of science and technology and the progress of the times, automation and intelligence have been popularized in manufacturing in all walks of life. With the progress of productivity, product defect detection has become an indispensable part. However, in practical scenarios, the application of supervised deep learning algorithms in the field of defect detection is limited due to the difficulty and unpredictability of obtaining defect samples. In recent years, semi-supervised and unsupervised deep learning algorithms have attracted more and more attention in various defect detection tasks. Generative adversarial networks (GAN), as an unsupervised learning algorithm, has been widely used in defect detection tasks in various fields due to its powerful generation ability. In order to provide some inspiration for the researchers who intend to use GAN for defect detection research. In this paper, the theoretical basis, technical development and practical application of GAN based defect detection are reviewed. This paper also discusses the current outstanding problems of GAN and GAN-based defect detection, and makes a detailed prediction and analysis of the possible future research directions. This paper summarizes the relevant literature on the research progress and application status of GAN based defect detection, which provides certain technical information for researchers who are interested in researching GAN and hope to apply it to defect detection tasks.

INDEX TERMS Deep learning, generating adversarial networks, defect detection, adversarial learning.

I. INTRODUCTION

Defect detection [1], which aims to find the appearance defects of various industrial products, agricultural products and construction roads, is one of the important technologies to ensure product quality and maintain production stability. Previous defect detection requires manual screening, which is costly and inefficient and difficult to cover large-scale quality inspection needs. In recent years, with the emergence of new technologies in industrial imaging, computer vision, deep learning and other fields, vision-based defect detection technology has made great progress and become an effective solution for product appearance inspection, which has aroused strong attention from academia and industry. Defect detection not only can be used to detect all kinds of industrial products (such as metal, textile, semiconductor, etc.), agricultural products (such as litchi, tomatoes, etc.) and building roads (such as concrete, road pavement, etc.) if there is a defect (various defect sample is shown in Fig. 1), and has good precision and efficiency, and can also provide a simple and

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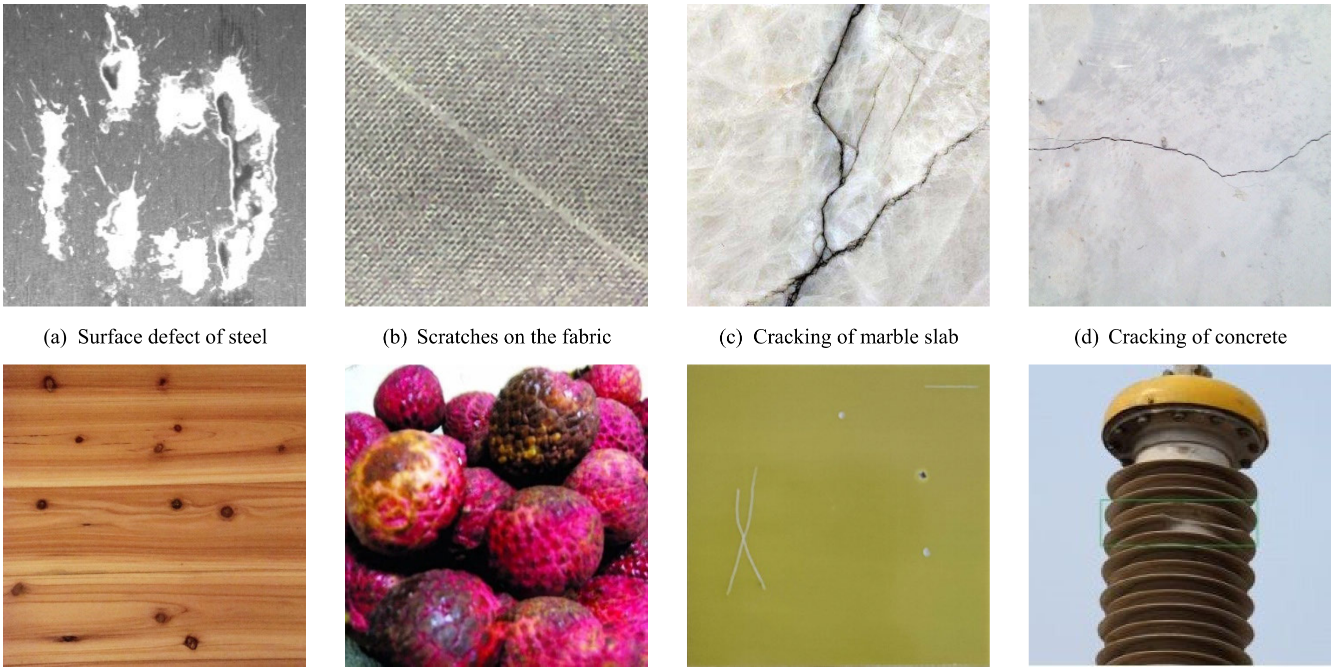


(a) Surface defect of steel (b) Scratches on the fabric (c) Cracking of marble slab (d) Cracking of concrete

(e) Surface defect of wood (f) Rotten litchi (g) Insulation separator defect (h) Breakage of insulator

FIGURE 1. Examples of surface images.

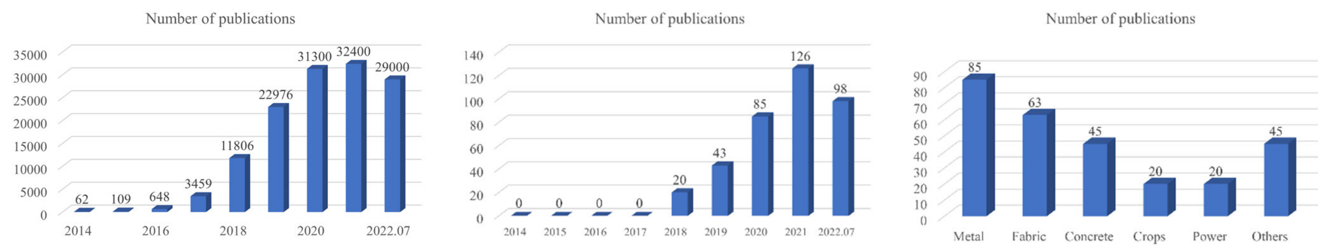
safe operation environment. Therefore, defect detection has become one of the important basic research and technologies in the fields of intelligent manufacturing, product storage and transportation management, and is widely used in scenarios such as unmanned inspection, intelligent inspection, production control and anomaly traceability. Vision-based defect detection not only has very important research value, but also has broad application prospects. However, compared with the general object detection task, the defect detection task is faced with many difficulties, such as lack of defect samples, low visibility of defects, irregular shape, unknown type, etc. This makes it difficult for many existing methods to meet the task requirements of high precision and high speed at the same time. Therefore, there are still a large number of problems to be solved on the way to realize practical application [2].

Because the defects on the surface of the object can be regarded as an ''anomaly'', some defect detection methods adopt the idea of anomaly detection. However, the definition of anomaly detection is different from defect detection. Specifically, the concept of anomaly detection is more extensive and abstract. Image-based anomaly detection mainly focuses on whether the input image is an anomaly instance, while surface defect detection focuses more on the detection task at pixel level. At the pixel level, anomalies differ more subtly from normal patterns and are much more difficult to detect. Therefore, the direct use of anomaly detection methods is difficult to meet the task requirements of surface defect detection [2].

Since deep learning methods have been applied to computer vision tasks, researchers have widely applied deep learning methods such as convolutional neural network (CNN) [3], Deep Belief Network (DBN) [4], Recurrent Neural Network (RNN) [5], Autoencoder (AE) [6] and Generative Adversarial Network (GAN) [7] to various defect detection tasks and achieved good performance. With the advent of the information age, data volume and complexity show an exponential growth trend. More and more deep learning methods and their variants have been proposed and applied to various defect detection tasks. In actual scenarios, it is often unrealistic to collect enough defect samples for deep defect detection. Usually, there are only a large number of normal samples and a small number (or even no) defect sample. In this case, the class imbalance problem [8] will be very serious, and even directly lead to the failure of defect detection task. Therefore, the data imbalance problem is the biggest obstacle to the practical application of deep defect detection method.

Due to the ability of distribution fitting, generative model has become one of the best methods for defect detection [9]. Among them, Variational Auto-Encoder (VAE) [10] and GAN (including their variants) are the most representative ones, and GAN and its variants are one of the most popular deep learning methods in recent years. The generative ability of GAN is excellent, and the generated image instances can even be indistinguishable from the real images. Fig. 2 shows the excellent defect generation capability of GAN, where the generated image examples are from literature [11]. As shown in Fig. 2, more realistic defect samples can be generated by training with a dataset containing only normal samples. The excellent generation ability of GAN alleviates the problem of insufficient defect samples to a certain extent [12].

FIGURE 2. An example of image generation based on GAN.



(a) Publication of papers on GAN (b) GAN-based publications in defect detection (c) GAN-based papers in typical defect detection

FIGURE 3. Papers on GAN and its application in defect detection were published from 2014.01 to 2022.07.

In addition, GAN can also learn the feature representation of the latent space by reconstructing (repairing) defect samples. And by comparing with normal samples, GAN can accurately detect whether there are defects in the graph and locate the location of defects. At present, most of the theories and methods based on GAN are suitable for defect detection. Therefore, GAN has become a very hot research topic in recent years. At present, many defect detection methods based on GAN have been widely used in production and manufacturing, construction, road and agricultural product quality inspection and other fields. Fig. 3 shows the publication of GAN-related papers and their application in defect detection from January 2014 to July 2022, where (a) cites the statistical data in literature [9].

Compared with many current literatures devoted to summarizing defect detection technology [13], [14], [15], [16], this paper makes the following contributions:

This paper focuses on the research progress and application status of GAN in defect detection. At present, many studies are devoted to summarizing the research progress and application status of defect detection, and comprehensively and profoundly summarizing the research progress and application status of deep learning-based defect detection. However, only a brief introduction is made to the research progress and application status of GAN in defect detection, without a comprehensive summary. Therefore, in this review, we review in detail the theoretical development and evolution of GAN, the research progress, development process and implementation of GAN-based defect detection methods in specific applications. In addition, this paper summarizes and prospects the latest progress, challenges and future research directions of GAN based defect detection, which is of great significance.

This paper can be divided into the following parts: Section 2 defines the defect detection problem and briefly introduces the defect detection process. Section 3 summarizes the defect detection algorithm based on GAN, including the principle of GAN, various variants and their development history in defect detection applications. Section 4 summarizes the application of GAN-based defect detection in various industries. Section 5 analyzes the limitations and existing problems of current GAN and GAN-based defect detection technology, and considers and looks forward to the next development direction of GAN and GAN-based defect detection based on the actual situation. Section 6 summarizes the thesis.

II. OVERVIEW OF DEFECT DETECTION

A. THE DEVELOPMENT OF DEFECT DETECTION TECHNOLOGY

The development milestones of defect detection methods are shown in Fig. 4, where the timeline indicates that this class

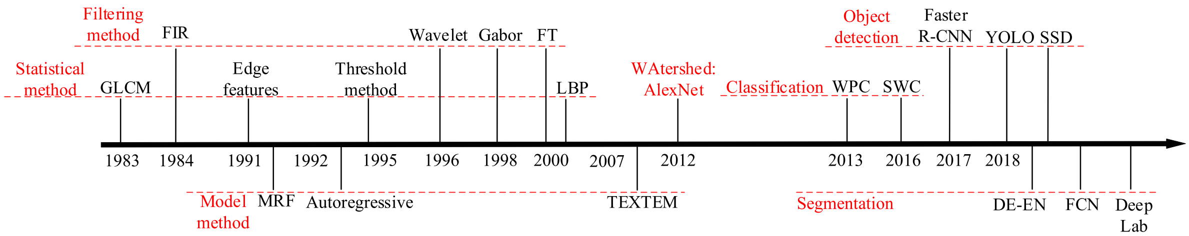


FIGURE 4. Development milestone of defect detection technology.

TABLE 1. Comparison of defect detection between traditional methods and deep learning methods.

Methods	Stands for model or algorithm	Advantages	Disadvantages
Traditional Mechanism	GLCM [18, 19], LBP [20, 21] FIR [22, 23], FT [24, 25] MRF [26, 27], TEXTEM [28, 29]	Low defect requirements, fast detection speed, less time consumption.	The intelligence degree is low, the applicable scope is narrow, the judgment defect limits much.
Deep Learning	CNN [2, 30] DBN [5, 31] AE [3, 32]	Automatic feature extraction, effective feature representation, scope of application.	It needs to occupy a lot of resources, including massive data sets, high cost of manual labeling, and a lot of computing resources.

of methods was first applied to defect detection. In Fig. 4, taking 2012 as the dividing line, existing defect detection methods are divided into traditional methods and deep learning methods. The research on defect detection based on traditional methods began in the 1980s, with abundant research results, which could be further divided into statistical method, filtering method and model method. And since 2013, with the successful application of deep learning technology represented by convolutional neural network in many computer-vision tasks, people have tried to apply it to defect detection and achieved rich results. In 2021, Su et al. [17] reviewed the surface defect detection based on visual perception, and made a profound summary of the application of traditional methods and deep learning methods in defect detection. Table 1 shows the comparison of the advantages and disadvantages of traditional methods and deep learning methods on defect detection. At present, research on defect detection methods based on deep learning methods is very active, and various innovative methods are constantly emerging. According to the different defect information obtained, they can be divided into whole image classification, object detection and pixel-by-pixel segmentation methods. And in the following sections, these methods are elaborated. methods are very active, and various innovative methods are constantly emerging. According to the different defect information obtained, they can be divided into whole image classification, object detection and pixel-by-pixel segmentation methods. in the following sections, these methods are elaborated.

B. DEFINITION OF DEFECT DETECTION PROBLEM

1) DEFINITION OF DEFECT

In computer vision tasks, defects tend to be notions of human experience rather than a purely mathematical definition. The difference in the perception of the defect pattern leads to two very different methods of detection. And take the insulation board surface defect detection as an example, as shown in Fig. 5. The first method is a defect detection method based on supervised learning [33], which uses defect images with labels (including categories, rectangular boxes, pixel by pixel, etc.) to be input into the network for training. In this case, ''defect'' means a marked area or image. Therefore, this method pays more attention to defect features, for example, in the training phase, regions containing continuous crack ranges or images are labeled as ''scratch'' defects for network training. And in the test phase, a ''scratch'' defect is considered to have occurred when a characteristic continuous crack is detected in the insulating partition image. The second is the defect detection method based on unsupervised learning [34], which usually only needs to input normal non-defect samples into the network for training, also known as one-class learning. This method pays more attention to the features without defects (i.e., normal samples). When features that have not appeared before (defect features) are found in the process of defect detection, defects are considered to be detected. In this case, ''defect'' means Anomaly, so this method is also called Anomaly detection.

2) DEFINITION OF DEFECT DETECTION

Compared with the explicit tasks of classification, detection, and segmentation in computer vision, the requirements for defect detection are very general. In fact, its requirements can be divided into three different levels, namely ''what is the defect'', ''where is the defect'', and ''how big is the defect''.

(1) Stage 1: ''What is the defect'', corresponding to the target classification/recognition task in computer

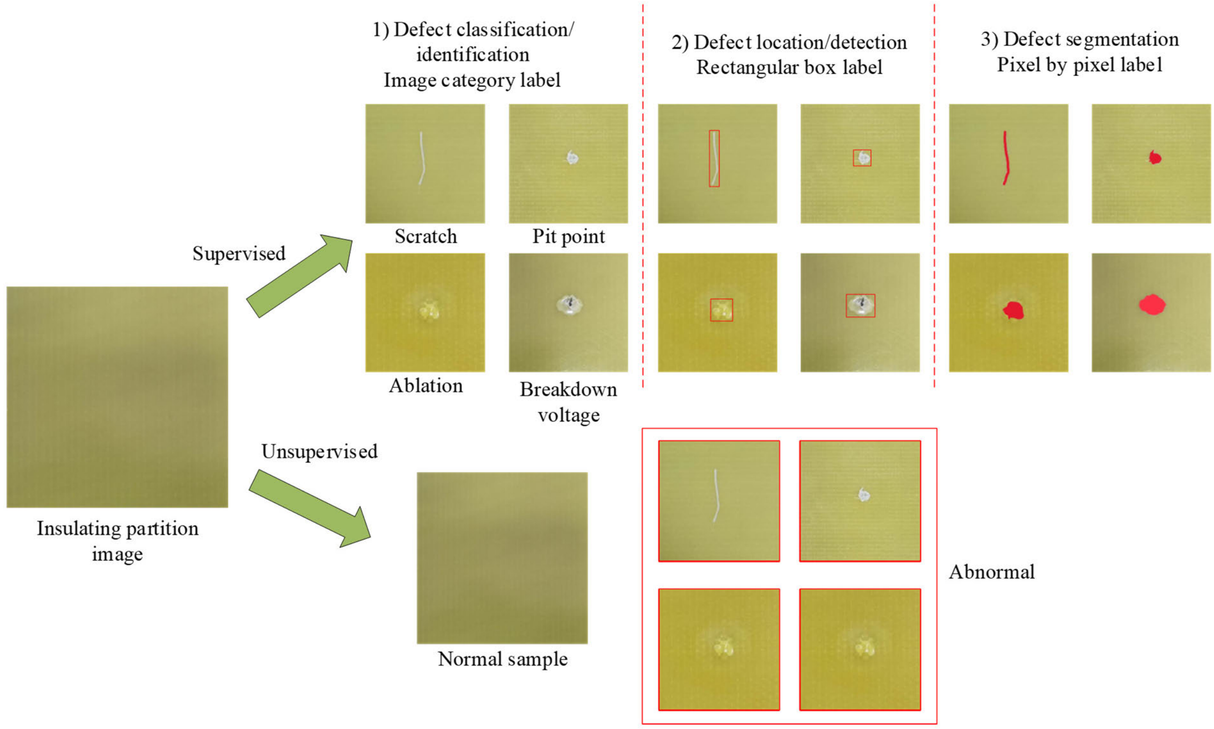


FIGURE 5. Example definition of a defect detection problem.

vision [35]. And as shown in Fig. 5, four defect categories are classified: scratch, pothole, ablation and voltage breakdown. The task at this stage is called "defect classification or recognition". Category labels include image labels and defect type labels, indicating whether the current image has defects and the category of defects respectively.

(2) Stage 2: "Where is the defect" corresponds to the target detection and localization task in computer vision [36], and the defect localization in this stage is detection in a strict sense. It not only gives the types of defects in the image, but also gives the specific location of the defects in the original image. As shown in Fig. 5, scratches, pits, ablation and voltage breakdown defects are respectively marked with external rectangular boxes.

(3) Stage 3: "How big is the defect", corresponding to the segmentation task in computer vision [37]. As shown in the defect segmentation area in Fig. 5, the defect is segmented from the background pixel by pixel, and a series of information such as the length, width, area and location of the defect can be further obtained, which can assist the product to carry out a higher level of quality assessment, such as the judgment of pros and cons of the product.

Although the functional requirements and goals of the three phases of defect detection are different, the three phases actually contain each other and can be inter-transformed. For example, the "defect location" in stage 2 includes the process of "defect classification" in stage 1, and the "defect segmentation" in stage 3 can also complete the "defect location" in stage 2. And Phase 1, Defect Classification, also achieves Phase 2 and phase 3 goals in a number of ways. Therefore, in the following, it is still referred to as defect detection according to the traditional industrial habits, and it is only distinguished for different network structures and target functions.

3) DEFECT DETECTION SYSTEM

The basic structure of the surface defect detection system based on deep learning includes three main modules, which successively complete the functions of image acquisition, image processing and image feedback [17]. In the image acquisition module, lighting and imaging system should be constructed according to the surface properties and defect features of the object to be detected. And through the cooperative configuration and operation of mechanical device, light source and camera, the surface image of the object to be examined with obvious defect characteristics is obtained. In the image processing module, the image processing algorithm is used to detect the defect target in the image and identify the defect type. Finally, in the image feedback module, the current sample is judged to be qualified according to the detection standard, and the judgment result is transmitted to the actuator. At the same time, the defect type, location, shape and size of the image can also be visualized and displayed, and the image and defect information can be stored for subsequent query and statistics. Deep learning-based defect

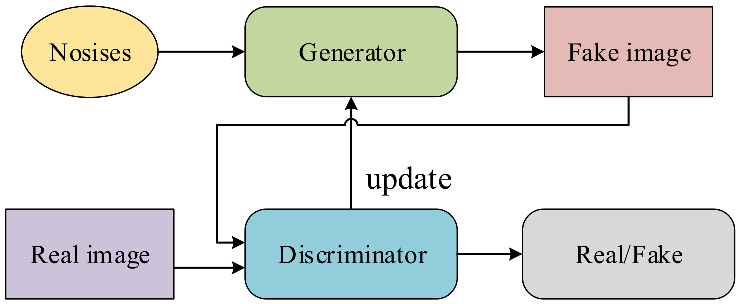


FIGURE 6. Structure illustration of the Generative Adversarial Network (GAN).

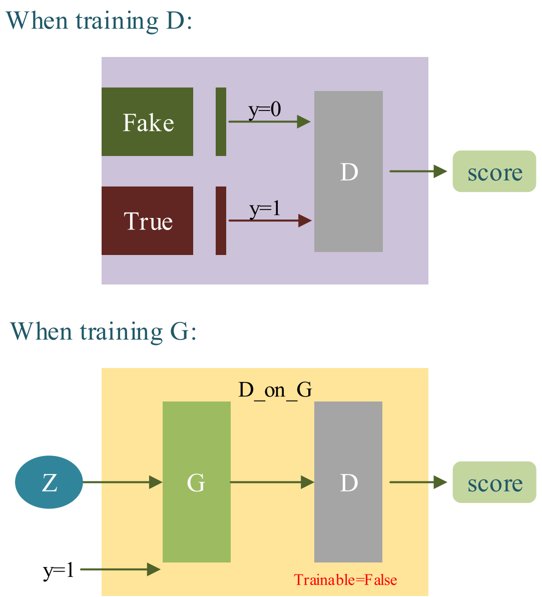


FIGURE 7. Training algorithm for GAN.

detection systems have been widely used in various detection tasks.

III. OVERVIEW OF GAN-BASED DEFECT DETECTION

A. OVERVIEW OF GAN PRINCIPLE

Goodfellow et al. [38] proposed generative adversarial networks in 2014, whose core idea is two-player zero-sum game theory. The generator and the discriminator use the mutual game strategy to continuously iterate to improve the effect. And the final effect you want to achieve is that the discriminator can't tell the difference between the real sample and the generated pseudo-sample. The network structure of GAN is shown in Fig. 6.

Generative adversarial network (GAN) consists of two important parts, namely, generator G and discriminator D. The generator G can generate pseudo samples whose similarity approximates the real samples by learning the feature distribution of the real sample data and random noise (or other data); And the discriminator D is used to distinguish between the real samples obtained from the data and the pseudo-samples generated by the generator G. The two models are iteratively optimized by continuous confrontation, that is, the optimization problem of GAN is a binary minimax adversarial problem, so that the data distribution of pseudo-samples generated by generator G is as close as possible to the data distribution of real samples. The final goal of GAN network optimization is as follows: generator G needs to be able to "fool" the discriminator, that is, generate spurious samples that make it difficult for the discriminator to distinguish between true and false; The discriminator D needs to distinguish real samples from generated samples as far as possible from the input data. The discriminator outputs "1" and "0" for real and generated samples, respectively. However, when the output probability of the discriminator is basically "0.5" each time (that is, the discriminator can no longer distinguish between true and false samples), it means that the model has reached the Nash equilibrium, that is, the optimal state, which is the adversarial thought of GAN. The training process of GAN can be divided into three stages, one is to fix the discriminator D and train the generator G, the other is to fix the generator G and train the discriminator D, and then cycle the first and second stages to continuously iterate the training. Fig. 7 shows the training algorithm for GAN.

The original objective function of the Generative adversarial network (GAN), as shown in Equation (1).

$$\min_G \max_D V(D, G) = \mathbf{E}_{\mathbf{x}\sim p_r(\mathbf{x})}[\log(D(\mathbf{x}))] + \mathbf{E}_{\mathbf{z}\sim p_z(\mathbf{z})}[\log(D(G(\mathbf{z})))] \tag{1}$$

where V represents the output value of the loss function. G and D are generators and discriminators for GAN, respectively. $P_r(\mathbf{x})$ is the real data distribution, $P_z(\mathbf{z})$ is the distribution of generated data, and $\mathbf{E}$ is the average.

The training optimization loss function of the generator G is shown in Equation (2).

$$\min_G V(D, G) = \mathbf{E}_{\mathbf{z}\sim p_z(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))] \tag{2}$$

The training optimization loss function of the discriminator D is shown in Equation (3).

$$\max_D V(D, G) = \mathbf{E}_{\mathbf{x}\sim P_r(\mathbf{x})}[\log(D(\mathbf{x}))] + \mathbf{E}_{\mathbf{z}\sim P_z(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))]P_z(\mathbf{z}) \tag{3}$$

When the quality of the generated samples is the best, the data distribution of the generated samples should be consistent with that of the real samples. Therefore, theoretically speaking, a trained GAN network should be able to fit the data distribution of any sample and determine whether a given new sample is in the distribution [9].

B. COMMON VARIANTS

In practice, how to find the Nash equilibrium of GAN network is a challenge and difficulty. Because GAN faces two major problems. First, the model is difficult to train and unstable. In the actual training, it is easy to have the discriminator D converge and the generator G diverge, and it is difficult to have good synchronization between the two networks. Therefore, the training of D and G needs to be carefully designed. Second, GAN has the phenomenon of mode collapse in the learning process [38]. When the generator G learns a parameter setting, it can generate samples that are very realistic to the discriminator D, and can easily "fool" the discriminator D; Therefore, generator G will generate the same pseudo-samples again and again, and eventually always generate the same sample points, and the pattern is missing, so it cannot continue to learn. In order to make GAN networks suitable for a wide variety of tasks and solve the problems there faces, researchers have proposed various variants based on GAN. Fig. 8 shows the various GAN variant networks that have emerged in recent years. The GAN variants that are more commonly used for defect detection are listed below.

CGAN [39]. Conditional Generative Adversarial Nets (CGAN) proposed by Mirza et al. is an extension of the original GAN. And both generator G and discriminator D condition on additional information $\mathbf{y}$, which can be any kind of additional information, such as category information or data from other models. Since labels, vectors and even images can be used as conditional data, CGAN can effectively control the sample semantics. CGAN is regarded as a two-player minimax game with conditional probability, and the objective function is defined as Equation (4). Literature [56], [57], [58] has introduced CGAN to improve its own network and method, which improves the accuracy and robustness of defect detection.

$$\begin{aligned}\min_G \max_D \mathrm{V}(D, G) &= \mathbf{E}_{\mathbf{x}\sim P_r(\mathbf{x})}\left[\log\left(D\left(\mathbf{x}|\mathbf{y}\right)\right)\right] \\ &+ \mathbf{E}_{\mathbf{z}\sim P(\mathbf{z})}\left[\log\left(1 - D\left(G\left(\mathbf{z}|\mathbf{y}\right)\right)\right)\right] \end{aligned} \tag{4}$$

DCGAN [40]. The DCGAN proposed by Radford et al. provides a convolutional GAN architecture. By using deconvolution to replace the pooling layer in generator G and stride convolutions to replace the pooling layer in discriminator D; And the batch-norm is used in generative model and discriminant model, which changes the activation function and makes GAN structure more stable. DCGAN verifies that discriminators can be used for feature extraction in supervised learning tasks and generators can be used for semantic vector computation. Literature [59], [60], [61] all introduced DCGAN to improve its own network and methods, which improved the accuracy and robustness of defect detection.

WGAN [46]. Arjovsky et al. proposed a new algorithm called WGAN. The original GAN performs model training by minimizing the JS divergence [62] between the real distribution and the generated distribution, but this difference cannot reach the optimum. However, by minimizing Wasserstein distance and satisfying Lipschitz continuity [62], WGAN theoretically solves the training instability and mode collapse problems of GAN and ensures the diversity of generated samples. And WGAN does not even need to elaborate the network architecture, the simplest multi-layer fully connected network can do. The loss function of WGAN is shown in Equation (5). Literature [63], [64], [65] has introduced WGAN to improve its own network and method, which improves the accuracy and robustness of defect detection.

$$\begin{aligned}\min_G \max_D V(D, G) &= \mathbf{E}_{\mathbf{z}\sim p_z(\mathbf{z})}[\log(D(G(\mathbf{z})))] \\ &- \mathbf{E}_{\mathbf{x}\sim p_r(\mathbf{x})}[\log(D(\mathbf{x}))] \\ &+ \lambda gp \mathbf{E}_{\hat{\mathbf{x}}\sim p(\hat{\mathbf{x}})}\left[||\nabla_{\hat{\mathbf{x}}} D\left(\hat{\mathbf{x}}\right)||_2 - 1\right] \end{aligned} \tag{5}$$

where $\hat{\mathbf{x}}$ is uniformly sampled in a straight line between a pair of real samples and generated samples, and λgp is a hyperparameter.

Cycle-GAN [49]. Zhu et al. proposed a method to learn to transform an image from the source domain to the target domain Y without pairwise examples. Cycle-GAN makes the inverse mapping from Y to X hold by introducing a cyclic consistency loss, namely $F(G(X)) = X$. The loss function change of Cycle-GAN is shown in Equation (6). This method has excellent performance in image style transfer, object deformation and photo enhancement. Moreover, Cycle-GAN has excellent performance in data enhancement. And literature [66], [67], [68] all introduced Cycle-GAN to improve its own network and methods, which improved the accuracy and robustness of defect detection.

$$\begin{aligned}\min_G \max_D V(G, D_Y, X, Y) &= \mathbf{E}_{\mathbf{y}\sim p_r(\mathbf{y})}[\log(D_Y(\mathbf{y}))] \\ &+ \mathbf{E}_{\mathbf{x}\sim p_r(\mathbf{x})}[\log(1 - D_Y(G(\mathbf{x})))] \end{aligned} \tag{6}$$

With the continuous improvement and deepening of deep learning theory, there is still a lot of research space for GAN variants in the future. Table 2 lists the optimization methods, advantages and disadvantages of some GAN variants, as well as the suitable application scenarios.

C. DEVELOPMENT OF DEFECT DETECTION BASED ON GAN

With the continuous deepening and improvement of GAN theory research, various variant network models emerge in endlessly. However, the defect detection based on traditional deep learning methods is limited by the difficulties of data collection and expensive labor costs. Inspired by the remarkable achievements of GAN-based anomaly detection, researchers gradually apply GAN and its variants to various defect detection tasks.

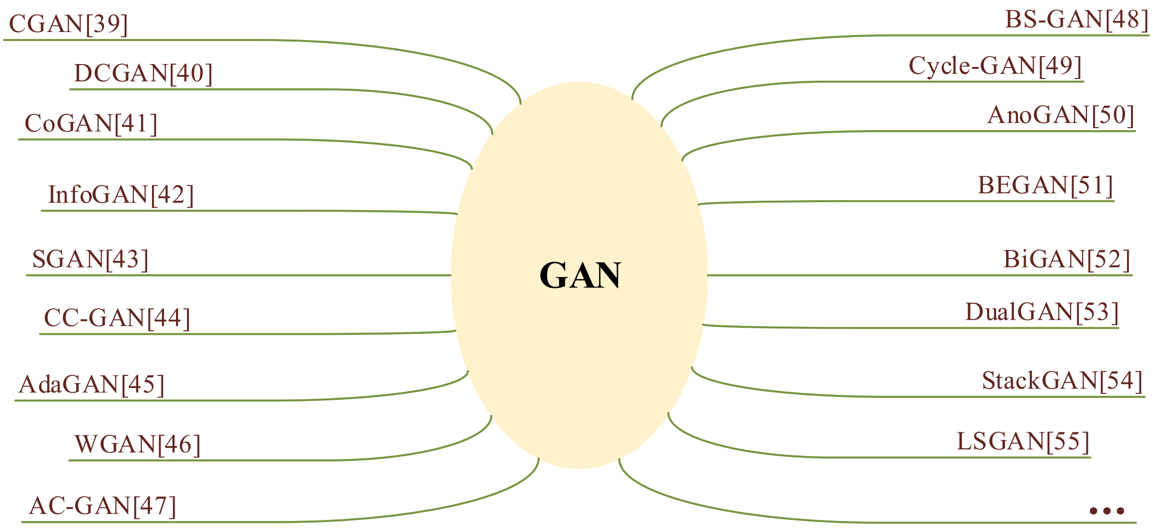


FIGURE 8. Examples of GAN variants.

Defects detection based on GAN mainly has the following three ideas:

(1) GAN network can learn feature distribution by repairing defect images, and then determine whether the sample has defects and locate the location of the defects by comparing with the input samples.
(2) Due to the scarcity of defect samples, GAN is used to generate defect samples and enhance the data set, so that the defect detection task can continue or even achieve better detection accuracy.
(3) Based on the network structure of GAN, by replacing the generator and discriminator with other networks, the generator directly detects defect samples, takes the detection results as the output of the generator, and then inputs the output of the generator to the discriminator, which improves and enhances it. Finally, the detection result of the discriminator is regarded as the result of defect detection.

In 2018, Zhao et al. [69] first proposed to apply GAN to defect detection. The basic detection concept is to establish a reconstruction network. If there are defect areas in the sample, these defect areas can be repaired, and then the input sample is compared with the recovered sample to indicate the accurate defect area. And based on this concept, Donahue et al. [70] first applied AnoGAN [50] to defect detection of electronic components in 2019. In the training, only normal samples are used to learn the feature distribution in the latent space unsupervised. The generator outputs the reconstructed image through forward propagation and compares it with the original image to detect the defect region. With the improvement of theoretical work, more and more researchers have applied GAN and its variants to various defect detection tasks. Fig. 9 shows the development of GAN based defect detection theory and application. For example, Liu et al. [71] designed a GAN-based single-class classifier for steel plate surface defect classification. Liu et al. [7] proposed a GAN-based supervised discriminant learning for fabric defect detection. And Cheng et al. [72] proposed a generative adversarial network with multi-head fusion strategy – IRT-GAN, which was used to automatically detect defects in composite materials using infrared thermal imaging technology. Based on the above content, there is still a lot of room for progress in defect detection of GAN, both its theoretical research and its application improvement will continue to move forward.

IV. OVERVIEW OF DEFECT DETECTION APPLICATIONS BASED ON GAN

Defect detection is a key problem and basic requirement in computer vision, but it is challenging to detect small and complex defects. And the defect detection is now widely used in industry, agriculture, construction and road, etc., and is playing an increasingly important role in quality detection in various fields. Today, GAN and their variants are trained to be widely used to detect a wide variety of defects, and as shown in Fig. 10, using these methods achieves better results than previous methods. At present, there are two main ideas for GAN based defect detection. Firstly, GAN skillfully uses the concept of game to train the generator and discriminator to detect the defect region successfully, and it does not need to know the real distribution of normal data. Second, GAN is used as a powerful means of data enhancement to expand the defect dataset. These advantages make GAN widely used in defect detection tasks. In the future, GAN will still be one of the hot spots in the field of defect detection.

In this section, we review GAN implementations for various defect detection tasks. In particular, it summarizes the key issues solved by GAN in these fields, and expounds the potential research directions of GAN, as well as the new challenges to be solved in the future. In recent years, deep learning technology has become the most successful application in industrial defect detection. The detector is obtained by training a large number of samples. The detector can perform automatic

TABLE 2. List of advantages and disadvantages of some GAN variants.

Methods	Improved point	Advantage	Insufficient	Application scenarios
CGAN [39]	Constraints are added to the original GAN model	Control GAN, clear sample generation direction	Training is erratic	Unsupervised learning Semi-supervised learning
DCGAN [40]	Convolution structure is introduced in generator and discriminator respectively	The applicability and stability of GAN are improved	The optimization method is not improved	Image generation
InfoGAN [42]	Adds a latent encoding of interpretability to random noise	Increase the interpretability of the GAN model and control the generation of images	High computational burden and lack of diversity in generated images	Image generation
WGAN [46]	Calculate the similarity between the probability distribution of the real data and the generated data through the Wasserstein distance	Resolved training instability and mode collapse issues, ensuring diversity of generated samples	The generated samples are of low quality and even difficult to converge	Used when the GAN model does not converge and the mode collapses
AC-GAN [47]	The generator inputs additional class labels, and the discriminator outputs two probability values	Guaranteed diversity and high resolution of generated images	The diversity of generated images relies on a large amount of training data	Image generation and classification
Cycle-GAN [49]	Increase the strength of the Propose a loop mechanism between two domains to implement transitions and constraints	Low requirements for data samples	Generates images with poor resolution and quality	Image style transfer, object deformation, photo enhancement
BEGAN [51]	The loss derived from the W distance to match the loss distribution of the autoencoder	Model convergence is fast, generator and discriminator training is balanced	Difficulty selecting hyperparameters	High quality image generation
BiGAN [52]	Combine the structure of encoder and discriminator to optimize, map the probability distribution of real data to latent space	Has good visual feature learning performance	The calculation of the optimization function is more complicated	Image generation
Stack GAN [54]	Superimpose two traditional GANs, high-resolution using a segmented training method	Generate high-resolution images	The generation failure caused by the training mode will occur	Text and Image Generation
LSGAN [55]	Replacing the cross-entropy loss function with a least squares loss function	Solved the problem of vanishing gradients and increased model stability	The diversity of generated samples may be reduced, and the generator may have gradient dispersion problems	High quality image generation

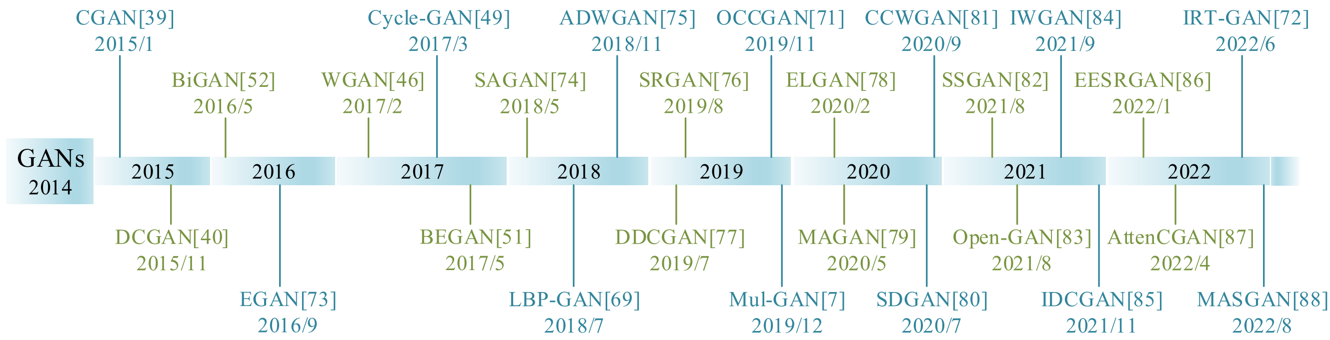


FIGURE 9. The development of GAN defect detection.

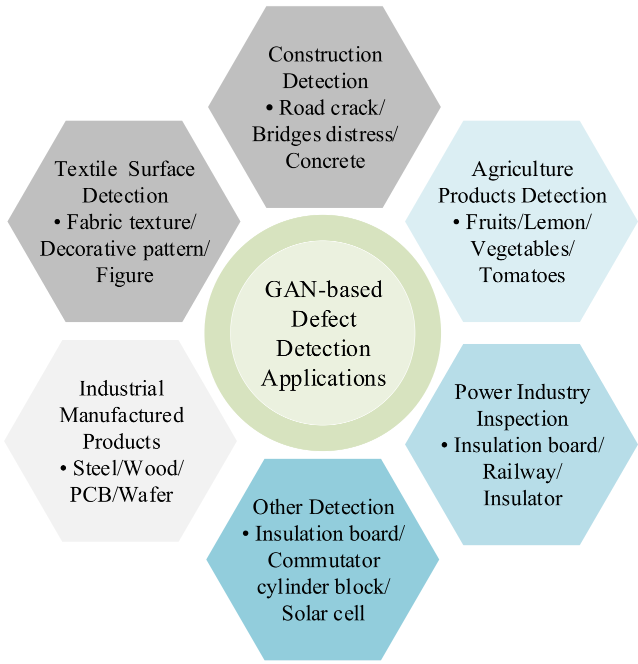


FIGURE 10. Application of defect detection based on GAN in various industries.

detection tasks such as product defects, abnormal operation of equipment, and fault diagnosis. At present, although deep learning techniques have been successfully applied to many industrial detection tasks and can achieve the most advanced performance, the defect detection task is still challenging due to the need for a large number of training samples and high-quality samples. The latest review of defect detection [13], [16], [89] points out that the three key issues of the current deep learning defect detection task can be summarized as follows:

(1) In the case of few or no actual defects, it is difficult for the detection model to correctly learn the feature representation, which is very difficult for the defect detection task based on deep learning methods.
(2) There are many types of defects, the model can't automatically identify the types of defects, and the labeling of new defects requires workers with expert knowledge and a lot of time.
(3) In actual industrial production, how to realize real-time and efficient detection is a difficult problem to be solved urgently.

In actual scenarios, it is difficult to collect enough defect samples, and the defect features extracted from insufficient and unbalanced data by deep learning methods are not accurate enough and even lead to the failure of the defect detection task. And the GAN can not only effectively alleviate the problem of lack of data by generating defective samples, but also detect defects by comparing the differences between input samples and reconstructed samples after learning to characterize normal samples. Therefore, GAN is widely used in various defect detection tasks. The following summarizes the application of GAN in defect detection in various fields, including quality detection of industrial products, textiles, construction roads and agricultural products.

A. OVERVIEW OF THE APPLICATION OF GAN BASED DEFECT DETECTION IN INDUSTRIAL PRODUCTS

In the process of industrial production, product defects are unavoidable due to improper manual operation, production technology problems, storage and transportation problems and other reasons. And the defect will affect the appearance and performance of the product and bring economic loss to the production enterprise. Strict control of the qualified rate of products can effectively reduce the company's production costs. In the visual defect detection of industrial products, based on the assumption that the potential features of normal samples and defect samples are different, GAN is used to obtain the feature distribution of normal samples in the potential space, and the trained model is used to detect defects. Generally, normal samples are only used for training GAN, and the combination of normal samples and defective samples is used for testing and verification.

In 2018, Zhao et al. [69] first proposed the combination of GAN and autoencoder for defect detection of industrial products. They proposed a defect detection framework based only on normal sample training, reconstructed defect images by combining GAN and AE, compared input samples with recovered samples, and accurately detected defect areas. In addition, this method does not require defect samples and manual labeling, and has high detection accuracy on DAGM2007 dataset [90]. Wang et al. [91] used the Otsu algorithm to determine the threshold of the residual image to repair the defect image, and then obtained the defect area by comparing the difference between the input image and the repaired image. Experimental results on engine cylinder head datasets show that the proposed method is effective in image restoration and defect detection.

Due to the shortage of defect images and high labeling cost in actual production lines, it is difficult to obtain sufficient diversity and quantity of defect data sets. Niu et al. [80] proposed a new generation method called Surface Defect Generative Adversarial Network (SDGAN). The defect images generated by this method have better image quality and diversity, and show excellent performance in detecting the surface defects of the cylinder block of the commutator. Moreover, the defect classification trained on SDGAN-enhanced images is robust to uneven and poor lighting conditions. SDGAN has two generators. One generator generates defective samples from normal samples, and the other generator restores defective samples to normal samples. In addition, four discriminators are used to distinguish real samples from generated samples. Lian et al. [78] combined GAN and CNN to automatically identify small defects in images. The network uses the changes in the image as regularization terms to generate defect-free images and corresponding enlarged defect images. This method expands the limited data set of defect detection training samples and achieves a defect detection accuracy of up to 99.2%.

In addition to the defect detection examples discussed above, Liu et al. [71] proposed a single-class classification method for strip surface defect detection based on GAN, and proposed a loss function to improve convergence speed and stability. Single-class classifier (OCC) can detect defects of different sizes, shapes and types only by training normal samples, and the average detection accuracy of the strip defect dataset reaches 94%. Zhang et al. [82] proposed a new method based on the idea of GAN, which is a semi-supervised generative adversarial network (SSGAN) composed of a dual attention mechanism segmentation network and a full convolution discriminator (FCD) network. To obtain more accurate segmentation results at pixel level. The segmentation network based on dual attention mechanism can segment defects from labeled and unlabeled images, while FCD uses adversarial and cross-entropy loss functions to generate confidence maps of unlabeled images in a semi-supervised learning manner. This method can achieve 81.8% defect segmentation accuracy on the Severstal steel plate defect dataset [92] with only 1/8 marks, and it is robust and flexible in various scenarios. In the latest research, GAN has also achieved excellent performance in glass fiber material defect detection [72], steel plate surface defect detection [88], and PCB board defect detection [86, 93]. Table 3 shows the research application and performance of GAN-based defect detection in the field of industrial production. Among all kinds of applications based on GAN defect detection, it is the most widely used in the industrial field and has made the most achievements. However, both in principle and application, there is still a large room for progress in the future.

B. OVERVIEW OF APPLICATION OF TEXTILE DEFECT DETECTION BASED ON GAN

In the process of manufacturing, transportation, storage and use, due to improper human operation or machine failure, textiles are likely to produce a variety of defects (such as scratches, pits, ablations and defects). With the continuous development of deep learning theory and technology, more and more researchers have applied GAN to textile defect detection, and achieved relatively outstanding results. The following is a review of recent studies on GAN applied to textile defect detection.

As early as 2018, Komoto et al. [94] proposed to use GAN for textile surface defect detection. They proposed Denoising autoencoder Generation Adversarial Network (DAE-GAN). By introducing adversarial learning framework into DAE, defective images can be restored to clearer defect-free images. However, there is no significant improvement in the accuracy of defect detection, so there is a large space for optimization. In order to improve the problem of low detection accuracy and difficult generalization when fabric texture and defects are complex, Liu et al. [7] proposed a fabric defect detection framework based on generative adversarial network, which can learn existing defect samples and adapt to different fabric textures. Firstly, a conditional GAN is trained to generate a reasonable defect patch, and then it is fused to a specific location. The network can update the existing fabric defect dataset and better detect the defects under different conditions. The final average detection accuracy reached 94.8%, the recall rate reached 97.6%, and the F-value reached 96.2%. Hu et al. [77] proposed a novel unsupervised automatic fabric defect detection method based on deep convolution Generative adversarial network (DCGAN). In this method, by introducing a new encoder component, the model will restore the defect image to a normal image, and then highlight the potential defect area through the residual error between the original image and the reconstructed image. Then the defect detection accuracy is improved by fusing the residual map with the likelihood map of the original image. Finally, this method can achieve 93.45% defect detection accuracy. To solve the problem of image distortion in textile defect detection, Li et al. [76] proposed SRGAN, a super-resolution image reconstruction technique based on generative adversarial network, which can reconstruct the obtained low-pixel image into high-pixel image. The generation network is responsible for generating high-resolution images, and the discrimination network is responsible for identifying the authenticity of images. The network is continuously optimized through generation loss and discrimination loss, and the generation of high-quality images is guided. Experimental results show that SRGAN can obtain clearer images, reconstruct richer textures, more high-frequency details, and identify defects more easily, which

TABLE 3. Research on defect detection application of GAN in industrial production field.

Tasks	Reference	Architecture	Datasets	Performance	Method
Surface texture defect detection	Zhao et al. [69]	GAN+AE	DAGM2007 [90]	Precision: 98.5323% Time: 52.1 ms	Unsupervised
Surface defect detection of engine cylinder head	Wang et al. [91]	GAN+Otsu	Engine cylinder head defect datasets	Precision: 95% (hole and bulge), 80%(scratch)	Unsupervised
Detection of surface defects of cylinder block of commutator	Niu et al. [80]	SDGAN	CCSD-L and CCSD-NL datasets	Error: 0.74%/1.77% IMP: 57.47%/49.43%	Semi-supervised
Surface defect inspection of steel plate, wood and tile	Lian et al. [78]	GAN+CNN	Steel plate, wood, and tile surface defect data sets	Precision: 99.2%	Supervised
Surface defect detection of strip steel	Liu et al. [71]	GAN+OCC	Strip surface defect data set	Precision: 94%	Unsupervised
Steel plate surface defect inspection	Zhang et al. [82]	SSGAN SegNet+FCD	Severstal steel plate defect datasets [92]	Precision: 81.8%	Semi-supervised

is very important in fabric defect detection. Zhang et al. [85] proposed an improved deep convolutional generative adversarial network, which introduced an autoencoder with an MLP layer in the generator module. By adding MLP layers to extract low-rank fabric image features, the model has a stronger ability to capture fabric texture features. Through the reconstruction of the defect image, the reconstructed image is compared with the defect image to segment the defect area. Compared with previous studies, this method can achieve better defect segmentation effect.

In the latest study, Li et al. [87] proposed a lightweight segmentation system for the detection of weak and small defects in fabrics. Firstly, the image repair mechanism based on generative adversarial network model is used to repair the defective sample images. Then, the difference between the defect sample and the fix sample is obtained. Finally, the defect region is segmented. The experimental results show that the joint intersection of three different datasets is 77.84%, 77.85% and 73.6%, respectively, and the proposed model is superior to the traditional semantic segmentation model. Wen et al. [95] proposed a new cyclic consistency Adversarial network with attention mechanism (ATTECGAN). First, defect samples were synthesized using ATTECGAN to expand the sample size. Secondly, by discovering the discriminative part of the samples and enlarging the differences between the samples, the attention mechanism is used to enhance the feature. ATTECGAN has been tested on KolektorSDD [96] and DAGM2007[90] datasets, and its accuracy is 98.53% and 99.57%, respectively, with only a small number of samples. The literature [97, 98, 99, 100, 101] all proposed fabric defect detection methods based on GAN, and achieved relatively excellent detection performance. Table 4 shows the research application and performance of GAN based defect detection in the field of textile quality inspection.

C. OVERVIEW OF GAN-BASED CONSTRUCTION ROAD DEFECT DETECTION APPLICATIONS

GAN is also gradually applied to defect detection in the construction industry, such as concrete surface, highway pavement, bridge surface, etc. Zhang et al. [11] proposed a Defect synthesis network Defect-GAN, which can generate real defects in various image backgrounds with different textures and appearance by introducing a strategy based on layer composition. It can also simulate the random variation of defects and flexibly control the location and category of defects in the image background. The experimental results on CODEBRIM dataset [102] show that defect-GAN has better performance than previous methods in Defect generation. The generated data sets are used in defect detection to achieve higher accuracy. Mei et al. [81] proposed a new road crack detection method, Conn-Crack, which combined conditional Wasserstein to generate adversarial network and connected graph, used 121 layers of densely connected neural network with deconvolution layer as generator for multi-level feature fusion, and used 5-layer fully convolutional network as discriminator. The method was tested on CFD dataset [103] and

TABLE 4. Research on the application of GAN in textile defect detection.

Tasks	Reference	Architecture	Datasets	Performance	Method
Fabric surface defect detection	Komoto et al. [94]	DAE-GAN	Textile defect dataset	Generate clear defect images Precision: 78%	Supervised
Fabric surface defect detection	Liu et al. [7]	CGAN+Mul-GAN	Image data set of flawless fabric	Precision: 94.8% Recall: 97.6% F1: 96.2%	Supervised
Automatic detection of fabric defects	Hu et al. [77]	DCGAN	Image data set of flawless fabric	Precision: 93.45%	Unsupervised
Solve the problem of image distortion in textile defect detection	Li et al. [76]	SRGAN	Textile defect dataset	A clearer fabric image is obtained and defects are easier to identify	Unsupervised
Fabric surface defect detection	Zhang et al. [85]	MLP+DCGAN	AITEX dataset [89]	Precision: 90.46%	Unsupervised
Fabric weak defect and small defect detection	Li et al. [87]	GAN	AITEX dataset [89]	IOU: 77.85%	Unsupervised
Fabric defect enhancement and detection	Wen et al. [95]	ATTECGAN	KolektorSDD [96] DAGM2007 [90]	Precision: 98.53%/99.57%	Semi-supervised

EdmCrack600 dataset. The results show that compared with other existing methods, the proposed method achieves the most advanced performance in terms of accuracy (96.79%), recall (87.75%) and F1 score (91.96%). To address the problem of data shortage and imbalance in building structural defects, Shin et al. [104] developed a data augmentation method using Generative adversarial networks (GAN). In the model experimentally applied with GAN-based data augmentation, the average performance is improved by about 0.16 compared to the model trained with small datasets. In order to solve the problem that it is difficult for CGAN to detect the shape of objects in the detection of road surface defects, Kyslytsyna et al. [105] proposed an improved CGAN with attention gate (ICGAN) method to detect road surface defects. ICGAN first removes any information in the image other than the road, then identifies flaws and adds two attention gates to the U-Net architecture to improve the segmentation capability of the generator in Pix2Pix. Experimental results on Unsupervised Llamas dataset [106] show that the ICGAN method has better performance than other state-of-the-art methods. In order to solve the problem of small sample size in intelligent road detection, Pei et al. [107] proposed a virtual image set generation method for asphalt pavement cracks based on improved deep convolution generative adversarial network. This method uses variational autoencoder (VAE) to encode real crack images. The latent variable values obtained from VAE are provided as input to the DCGAN model generator, and the model hyperparameters are optimized. Then, the Adaptive moment estimation (Adam) optimizer is used to reconstruct the optimization model, so as to improve the convergence speed and generalization ability of the model.

In the latest study, Xu et al. [108] proposed a method to detect pavement cracks under small samples. Firstly, the image generated by GAN model is used to expand the original small sample dataset, and convolutional neural network (CNN) model is constructed at the same time. Then, the transfer learning method is used to train and test the data sets before and after the extension, respectively to verify the validity of the extended data. It is proved that, compared with the unexpanded dataset, the CNN model trained after the expansion improves the detection accuracy of the test set from 80.75% to 91.61%. Ali et al. [109] proposed a new sensor technology that can detect road damage using a deep learning-based image processing algorithm. This technique includes a super-resolution semi-supervised learning method based on generative adversarial networks. The former improves the quality of the road image and makes the damaged area clearly visible. The latter uses 5327 road images and 1327 tag images to enhance the detection performance. The two methods are applied to four lightweight segmentation neural networks. For 400 road images, the average recognition rate reached 81.540% and 79.228%, respectively. Literature [110], [111], [112], [113], [114] has also made improvements and upgrades for GAN used in construction defect detection. Table 5 shows the research application and performance of GAN-based defect detection in the field of construction road quality inspection.

D. OVERVIEW OF GAN-BASED APPLICATION IN DEFECT DETECTION OF AGRICULTURAL PRODUCTS

In recent years, researchers have also used GAN for surface defect detection of agricultural products, so as to control the quality of agricultural products and improve economic benefits. In 2019, Tian et al. [117] used the Cyclic Consistency Adversarial Network (Cycle-GAN) deep learning model to achieve data enhancement in the detection of Apple anthracnose lesions, and achieved higher detection accuracy compared with the dataset without data enhancement. Abbas et al. [118] proposed a deep learning-based method for tomato disease detection, which uses conditional generation adversarial network (CGAN) to generate synthetic images of tomato plant leaves. Then, transfer learning was used to train the DenseNet121 model on both synthetic and real images to classify tomato leaf images into ten categories of diseases. The proposed model has been extensively trained and tested on the publicly available Plant Village dataset [119]. The method divided tomato leaf images into 5 categories, 7 categories and 10 categories, with the accuracy of 99.51%, 98.65% and 97.11%, respectively. The proposed method is shown to be superior to the existing methods. Wang et al. [120] adopted a transformer-based generative adversarial network (GAN) as a data enhancement means, which can effectively enhance the original training set with more diverse samples to rebalance the three categories. Experimental results show that the enhanced data sets get higher detection accuracy. In order to alleviate the problem of data scarcity, Brid et al. [121] adopted conditional GAN to synthesize images to enhance the dataset (Lemons Quality Control Dataset [122]), and finally achieved 88.75% defect classification accuracy. Even if the model is compressed to half the original size, the conditional GAN enhanced classification network can maintain the classification accuracy of 81.16%. Guo et al. [123] adopted a data expansion method combining deep convolution generative adversarial network and rigid transformation (RT) to improve the data richness of defective dates and effectively solve the imbalance problem among different types of date data. The defect detection accuracy after data enhancement is up to 99.2%. Chen et al. [124] proposed an automatic defect detection method based on YOLOv4. Cycle-GAN in this method contributes the most to the model training strategy. The pseudo-defects generated by Cycle-GAN enrich the types of defects, and the patches can conform to the texture after pasting to the original position, and the patches can be automatically labeled, which greatly improves the performance of YOLOv4 defect detection.

Table 6 shows the research application and performance of GAN in fruit crop defect detection.

V. ISSUE DISCUSSION AND FUTURE OUTLOOK

GAN network has made remarkable achievements in the field of computer vision due to its powerful generating ability and "coincidence" with the era of big data. Although GAN has been widely used in defect detection, there are still many challenges, and it still has broad application prospects in the future. This section summarizes the challenges and possible future directions of GAN-based defect detection.

The old problems [125] in the application of GAN network, such as mode collapse, gradient disappearance and training instability, have not all been solved. Although various variants have emerged, each of these networks basically focuses on improving only one or two problems, leaving the remaining problems unimproved and possibly even more serious. For example, CGAN [39] added constraints to the original GAN model, making GAN generation direction controllable, but the training of the model was still unstable. WGAN [46] used Wasserstein distance to break through the traditional defects of GAN and make the model training more stable, but also prone to the phenomenon of gradient dispersion. LSGAN [55] improved the loss function to the least square loss, which improved the quality of the generated samples, but the model was still prone to the problems of gradient disappearance and gradient explosion. By sorting out various problems existing in GAN itself and summarizing the defect detection methods based on GAN, future research on generative adversarial network and its potential breakthrough in the field of defect detection should mainly focus on the following aspects.

A. GAN ITSELF

1) THEORETICAL EXPLORATION

The main purpose of theoretical research is to solve the defects of GAN model, but the existing methods are mainly to adjust the training parameters and modify the training process, and the theoretical exploration of the defects of GAN is not deep enough. Therefore, researchers should pay attention to the structural design of the basic algorithm and the design of application-oriented loss function to make theoretical breakthroughs. For example, we can pay attention to the variation of traditional structure, such as CGAN network, and combine the advantages of existing algorithms to improve the model architecture, and design general and reasonable constraints, so as to ensure that under the condition of model stability, we can pay attention to the loss function design with good quality and diversity of image generation. The theoretical exploration of GAN is one of the main development directions in the future.

2) INTERNAL MECHANISM TRANSPARENCY

Compared with machine learning, the model complexity of deep learning increases by orders of magnitude, and the

TABLE 5. Research on defect detection application of GAN in construction road industry.

Tasks	Reference	Architecture	Datasets	Performance	Method
Concrete defect data enhancement	Zhang et al. [11]	Defect-GAN	CODEBRIM dataset [102]	The data set is expanded and the defect detection accuracy is improved	Unsupervised
Road crack detection	Mei et al. [81]	WGAN+FCD	CFD dataset [103]/ EdmCrack600 dataset	Precision: 96.79% Recall: 87.75% F1: 91.96%	Supervised
Solve the shortage and imbalance of building structural defects data	Shin et al. [104]	GAN	Concrete surface defect dataset	The average performance improvement is about 0.16	Semi-supervised
Road surface defect detection	Kyslytsyna et al. [105]	CGAN	Unsupervised Llamas dataset [106]	Precision: 88.03% Recall: 90.06% F1: 85.01%	Unsupervised
To solve the problem of small sample size in intelligent road detection	Pei et al. [107]	VAE+DCGAN	CIFAR-10 dataset [115]	Realistic defect images are generated and the dataset is expanded	Unsupervised
Pavement crack detection	Xu et al. [108]	GAN+CNN	SDNET2018 dataset [116]	The detection accuracy increased from 80.75% to 91.61%	Supervised
Road damage detection	Ali et al. [109]	AGAN+IDSNet	Road damage image dataset	Precision: 90% Recall: 95.2% F1: 94.1%	Unsupervised

training and computation process is "hidden" and untraceable, making it particularly important to study the inner working mechanism of models. Using appropriate tools to realize the transparent research of the working mechanism of the information flow inside the model, we can find the problems affecting the stability and training process of the model from the root, and then analyze and solve them to break through the performance bottleneck of the model. Using appropriate tools to realize the transparent research of the working mechanism of the information flow inside the model, we can find the problems affecting the stability and training process of the model from the root, and then analyze and solve the problems, so as to break through the performance bottleneck of the model. In particular, it is urgent to solve the representation problem of how GAN model generates images and the visualization problem of global convergence of generator and discriminator. In addition, the controllability problem of the generated network has not been completely solved, and only the experimental effect of specific scenes has been achieved, but the universality of different scenes of the control effect has not been achieved. Transparency research on the internal mechanism of GAN is also an important development direction.

B. DEFECT DETECTION DIRECTION

1) NETWORK MODEL REPLACEMENT

In the improvement of GAN model, the use of other network replacement generators and discriminators should be considered in the future. In other words, based on the structure of GAN network, the idea of GAN network is still followed, and various networks are used as generators and discriminators. For example, SSGAN [82] replaced the generator of traditional GAN with Semantic Segmentation Network (SegNet) and discriminator with full convolution discriminant network (FCD), which directly avoided the problems existing in GAN model and achieved good performance in strip defect detection. This is also a method that can directly avoid the problems of pattern collapse, gradient disappearance and training instability in GAN, which is worth further study in the future.

2) INTRODUCING ATTENTION MECHANISM

Attention mechanisms [126] are derived from the study of human vision. In cognitive science, due to information processing bottlenecks, humans selectively focus on a portion of all information while ignoring other visible information. Attention mechanism in neural networks is a resource

TABLE 6. Application of GAN in defect detection of agricultural products.

Tasks	Reference	Architecture	Datasets	Performance	Method
Detection apples for anthracnose lesions	Tian et al. [117]	Cycle-GAN	Apple lesion image datasets	Precision: 95.57%	Supervised
Detection of tomato diseases	Abbas et al. [118]	CGAN	Plant Village dataset [119]	Precision: 99.51%/98.65%/97.11%	Semi-supervised
Surface defect detection of litchi	Wang et al. [120]	Transformer-GAN	Litchi defect dataset	Precision: 92.76%	Unsupervised
Lemon defect classification	Brid et al. [121]	CGAN	Lemon quality control dataset [122]	Precision: 88.75%	Unsupervised
Jujube surface defect detection	Guo et al. [123]	DCGAN	Date defect dataset	Precision: 99.2%	Supervised
Surface defect detection of pineapple	Chen et al. [124]	Cycle-GAN	Pineapple defect image dataset	Validation AP: 90.94%	Supervised

allocation scheme to allocate computing resources to more important tasks and solve the problem of information overload when computing capacity is limited. In neural network learning, generally speaking, the more parameters of the model, the stronger the expression ability of the model, and the more information stored in the model, but this will lead to the problem of information overload. By introducing attention mechanism, the problem of information overload can be solved and the efficiency and accuracy of task processing can be improved by focusing on the information that is more critical to the current task, reducing the attention paid to other information, and even filtering out irrelevant information. By introducing attention mechanism into GAN network, especially in the generator part, the model pays more attention to the defect feature part, which may improve the feature learning and generation ability of generator. Therefore, the introduction of attention mechanism in GAN is one of the directions that can be further studied in the future.

VI. CONCLUSION

This paper reviews the research progress, development history and application status of GAN based defect detection. Through the thinking and definition of defect and defect detection, this paper discusses the implementation scheme of current defect detection system, summarizes the principle of GAN, and briefly introduces and compares various variants of GAN, and expounds the theoretical development and application status of defect detection based on GAN. This paper also introduces the research progress and application status of GAN defect detection methods in various fields in detail. In view of the outstanding problems in the development and application of GAN and GAN-based defect detection technology, the possible research directions and improvement ideas in the future are put forward. We hope that this review will be helpful to researchers working on GAN, especially those who are interested in using GAN for defect detection tasks. We believe that with the innovation of various theories and the iterative development of technology, the defect detection technology based on GAN will enter a new era of development.

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