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# *Progress and Analysis of Electronic Component Data Augmentation Based on GAN, Diffusion Models, and Flow Models*

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***Abstract.*** With the rapid development of the electronic manufacturing industry, there are higher requirements for automation in the recognition and defect detection of electronic components. However, the difficulty in obtaining defect samples of electronic components and the serious imbalance between positive and negative samples have for a long time restricted the generalization ability of deep learning detection models. The application of generative models for data augmentation has developed into an important way to tackle this challenge. This paper focuses on the applications of three types of generative data augmentation techniques in electronic component images, namely generative adversarial networks (GANs), diffusion models and flow models. For each category, it systematically examines the fundamental principles and their applications in the electronic component situation and carries out comparative analyses in terms of generation quality, training stability and the like. The results show that GAN can rapidly generate samples but has problems of mode collapse and edge distortion. The diffusion model shows strong ability in generating high-resolution images yet encounters bottlenecks in industrial real-time performance. The flow state model which can accurately estimate the density and maintain the structure still has its potential that has not been fully explored in the electronic component field yet.

***Keywords:*** generative models, diffusion models, normalizing flows, electronic components

## 1. Introduction

Electronic components (printed circuit boards, capacitors, diodes) are widely used in various industrial fields. Ensuring the high quality of these components during industrial production is of vital importance. Due to the high precision of electronic components, even minor surface defects can lead to functional failures and cause inevitable economic losses. Therefore, automated inspection has become an indispensable part of controlling the quality of electronic manufacturing in the context of Industry 4.0 [1].

In recent years, deep learning methods, with convolutional neural networks (CNNs) being the most representative, have performed exceptionally well in defect detection tasks. By leveraging such deep learning approaches, the need for manual inspection can be effectively eliminated [2]. The

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performance of deep learning models requires large and well-annotated training sets to develop the ability to learn Automated operations are carried out starting from the original image. Actually, the situation is not always like this. Under the background of electronic manufacturing, the defect samples that are extremely rare and some defect types that only appear under specific production conditions. This situation directly results in a severe imbalance between the number of normal samples and defective samples, thus causing the improvement of the model's generalization ability to slow down then.

Traditional data augmentation techniques, like simple geometric transformations (rotation, scaling) and pixel-level adjustments (brightness adjustment, contrast enhancement), have been widely used to initially relieve the problem of sample scarcity [3]. Although these methods have a low threshold and are easy to operate, they cannot fundamentally generate new samples. The traditional methods only convert the existing images and do not develop new defective styles. As the complexity of printed circuit board layout and component design continuously increases, there emerges an ever - widening gap between the demand for detection models and the supply of traditional data - augmentation methods.

A generative model provides a completely different yet effective approach. Instead of transforming existing samples, it is to learn the latent data distribution so as to synthesize new pictures. Three generative models that have obtained a significant amount of research attention are generative adversarial networks (GANs), diffusion models and also flow - based models. With the adversarial training framework of generators and discriminators, generative adversarial networks (GANs) are utilized to rapidly generate samples [4]. Through the process of forward adding noise and reverse removing noise, diffusion models are used to generate high - fidelity images [5].The flow model, by way of reversible transformations, establishes an accurate mapping between data and the latent distribution in accordance with [6]. Each approach has its own distinctive merits and limitations within the field of electronic components.

Although there is a continuous increase in the interest in generative data augmentation across various domains, the existing reviews still lack a systematic comparison of these three models in the context of electronic components. This paper intends to fill this gap by carrying out a comprehensive review and comparative analysis of these three data augmentation methods.

## 2. Data augmentation of electronic components based on GAN

### 2.1. Overview of the basic principles of GAN

Proposed first by Goodfellow et al., generative adversarial networks (GANs) are the ones that contain two neural networks and are trained simultaneously through a minimax zero-sum game [7]. The generator G generates a synthetic image from the randomly - noisy vectors z sampled from the prior distribution, while the discriminator D tries to distinguish the real samples and the generated samples. The specific formula can be expressed as:

$$\underset{G}{min}\underset{D}{max}\mathbb{E}_{\mathbb{x}\sim\mathbb{p}_{dt}(\mathbb{x})}\left[logD\left(x\right)\right]+\mathbb{E}_{\mathbb{z}\sim\mathbb{p}_{z}(\mathbb{z})}\left[log\left(1-D\left(G\left(z\right)\right)\right)\right] \tag{1}$$

During the adversarial process the generator continuously enhances its performance when reaching equilibrium the distribution of the sample data generated by the generator in theory is the one matched with that of the real samples.

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### 2.2. Application in electronic component image enhancement

In the field of electronic component detection, GAN has multiple advantages. It can quickly generate samples through a single inference mechanism. Moreover, certain versions of GANs allow users to directly specify defect types and even severity levels when generating samples. This kind of controllability is extremely useful when it comes to supplementing specific defect samples for some particular working conditions. At present, the data augmentation technology based on GANs have been extensively applied in electronic components. A TransGAN (cTransGAN) framework specifically crafted for PCB electronic component detection has been proposed by Wang and his team [8]. A dataset which contains optical couplers, capacitors, and diodes is also produced by them. The result shows that the training set enhanced by cTransGAN exhibits a considerable improvement in the three detection frameworks. Moreover the generated samples not only increase the quantity of the training data but also enrich the diversity of the data enabling the detection model to capture more semantic features. This research shows that the data augmentation technique based on GANs can effectively improve the accuracy of electronic component recognition.

In the semiconductor manufacturing field, Yen and the others have applied CycleGAN to the data augmentation of scanning electron microscope (SEM) images in order to strengthen the classification of integrated circuit defects [9].In this situation, the unpaired image-to-image translation ability of CycleGAN is quite important because it is extremely hard to get completely paired defect and non-defect images in actual semiconductor manufacturing. The expanded dataset has enabled the classification model to achieve an AUC value of 99.88 on the ADI CD - SEM dataset, which firmly demonstrates the effectiveness of the GAN - based image conversion technology in the application of industrial microscope images indeed.

The main benefit of the data augmentation method grounded on generative adversarial networks (GAN) is the high efficiency of the inference procedure. Once trained, the generator of GAN is able to generate samples through a single forward propagation, which is especially suitable for batch acquisition of defect samples so as to alleviate the situation of insufficient defect samples in industrial scenarios. However, there are still quite a number of limitations when applying generative adversarial networks (GAN) to electronic component data augmentation. GAN encounters a problem named mode collapse and fails to present details quite well, which can cause the defective samples to be blurry and all to appear the same, truly spoiling the usability of the generated samples as Bond-Taylor and the others have pointed out. A comprehensive analysis has been made on these issues, showing that generative adversarial networks (GANs) usually encounter problems in copying fine textures and keeping structural consistency [10]. In the high-precision industrial environment, even the tiniest edge deformations or blurred pin outlines can lead to the training effect becoming worse. So then, although generative adversarial networks (GAN) can quickly generate samples, in some applications of high-precision electronic components, there may indeed be a lack of the ability to produce high-fidelity data augmentation.

## 3. Data augmentation of electronic components based on diffusion models

### 3.1. Overview of the basic principles of diffusion models

Diffusion models are a type of generative model that produces new samples through a gradual denoising process. This framework consists of two complementary stages: forward diffusion and reverse denoising. In the forward process, Gaussian noise is gradually added to a normal, intact

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image, gradually blurring it until it is completely covered by random noise. This process can be represented as:

$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, \quad \epsilon \sim N(0, I) \tag{2}$$

Where $\bar{\alpha}_t$ is the accumulated noise scheduling coefficient and $\epsilon$ is the standard Gaussian noise. Correspondingly, the neural network is trained to predict and eliminate noise at each step, thereby gradually reconstructing a complete and clean image from pure noise:

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \epsilon_\theta (x_t, t) \right) + \sigma_t \epsilon', \quad \epsilon' \sim N(0, I) \tag{3}$$

The noise prediction network is learned by $\epsilon_\theta$ and $\sigma_t$ controls the randomness of the reverse step. This iterative optimization mechanism, which by gradually denoising recovers more and more refined features, generates extremely detailed and lifelike images.

### 3.2. Application of diffusion models in generating defective images of electronic components

For electronic component images, this gradual denoising mechanism is actually quite advanced. In the task of generating samples with tiny defects and complex texture details, it is expected to precisely reconstruct and synthesize, providing high-quality training data for defect detection models. Conditional diffusion variants can also support the directed generation of specific defect types, which is particularly crucial in addressing the imbalance of positive and negative samples in industrial datasets.

A set of rather credible experimental data was produced through the research of Dhariwal and Nichol. After the introduction of classifier guidance, the diffusion model still has an advantage over generative adversarial networks (GANs) in respect of distribution coverage, and the FID metric is also more outstanding [11]. Taking the LSUN bedroom 256×256 benchmark as an example, a diffusion model has generated a FID value that is 1.Well, under the same testing conditions, the best result of the generative adversarial network (GANs) remains at 2.35.For the data augmentation of electronic component images, this conclusion indicates that, in those industrial image enhancement tasks with strict requirements on detail fidelity and defect texture recovery, the diffusion model is indeed a rather suitable option.

In the field of electronic components, Xu et al. combined ControlNet with stable diffusion models to expand the PCB surface mount component dataset [12]. The research subjects included resistors, diodes, and potentiometers, among other electronic components, which itself indicates that the application scope of diffusion models is not limited to a single defect category, but can also be applied to multi-category mixed detection scenarios. Of course, the authors did not ignore the practical problems - they admitted in the paper that for diffusion models to be truly effective in the PCB scenario, both the condition control strategy and the structural design of the downstream detection network are indispensable, and there is still much room for optimization in the deployment stage.

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Croitoru et al. reviewed the applications of diffusion models in image generation, super-resolution, restoration, and semantic editing [13]. When these capabilities are combined, it is not difficult to find that diffusion models are actually very suitable for the methodological aspect of electronic component image enhancement, as structural consistency and the fidelity of local defects are key points that cannot be ignored in such enhancements.

Diffusion models do show many advantages in the data augmentation of electronic components. The samples they generate have rich textures, coherent structures, and detailed realism. However, they also have an inescapable core shortcoming, which is the inference speed, and the speed gap compared to GANs is very large. Accelerated sampling strategies like DDIM do significantly reduce the number of iterations, but even so, the generation speed is still a notch below that of GANs. In addition, training diffusion models on high-resolution images requires a large amount of GPU memory and computing time, which may exceed the hardware capabilities of actual industrial environments and cannot meet the high real-time requirements of industrial scenarios.

## 4. Data augmentation of electronic components based on flow models

### 4.1. The principles and characteristics of flow models

Flow-based generative models by constructing a series of reversible transformations, maps complex data distributions to simple distributions, usually the standard Gaussian distribution, and the specific formula can be expressed as:

$$logp\left(X\right)=logp\left(z\right)+log\left|detJ_{f}\left(X\right)\right| \tag{4}$$

Where $z=f(x)$ is a reversible transformation from the data space to the latent space, $p(z)$ is a simple distribution. The flow models that have reversibility and explicit probability modeling ability make the precise calculation of data likelihood actually possible. When the two core characteristics of the flow model, which are reversibility and the clear probabilistic modeling ability, are combined, the precise calculation of data likelihood becomes feasible. Interestingly the flow model can perform two tasks with the same network without switching density estimation which is mapping data to the latent space and sample generation which is mapping latent vectors back to the data space. The capability of this bidirectional mapping is particularly important in applications related to electronic components the forward mapping can assist in determining whether the generated samples conform to the learned data distribution and the reverse mapping can directly generate new samples. This mechanism that does have quite obvious advantages, when it comes to generating samples, can not only retain structural information but also make use of clear density estimation to figure out how close these samples are to the real distribution according to Lipman et al. There is a proposal of the flow matching technique that transforms the training problem of the generative model into a vector field matching problem so as to make the training process become simple. Therefore theoretically speaking this technology has a relatively high sampling efficiency [14] the research analysis emphatically points out that the flow model provides a principled framework for precise inference in probabilistic modeling which can construct probability distributions through reversible transformations to precisely describe the data distribution.

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### 4.2. Applications in industrial and electronic component scenarios

Yu and others, by means of flow models for industrial anomaly detection, rely on FastFlow that makes use of two-dimensional regularized flows for unsupervised anomaly detection in accordance with [15]. This research also demonstrates through feature visualization that the flow model has the capability of reversible mapping from visual features to the probability space and then back to visual features, which indicates that they are not only able to be used for anomaly detection but also have a certain degree of structural fidelity. Regarding the image data augmentation of electronic components, this means that flow models are highly suitable for defect generation and quality verification tasks that require stable spatial structures such as pins and solder joints and so on. Albergo and Vanden - Eijnden have studied the connection between regularized flows and random interpolation, and provided a unified framework to understand the generation based on flow and diffusion models [16]. This theoretical insight that is of great significance to the electronic component field shows that the boundaries among these generative models are indeed becoming increasingly blurred.

In the task scenario of electronic component data augmentation, the flow model has quite a number of rather suitable characteristics. There is an obvious data feature of electronic component images, the proportion of defective samples is extremely low, and the components themselves have a very regular structural arrangement and abundant texture details. Well, the flow model happens to be especially good at precise density estimation and robust structured generation, and thus is naturally in line with it. In addition, modern flow architectures such as flow matching show good inference speed and only need one forward pass during generation. Although there are these advantages, flow models still have some limitations in the field of electronic component data augmentation. There is rather little application research that specifically targets electronic component images. Although process models perform well in industrial anomaly detection, the potential of them as generators of electronic component defect data has not been fully explored yet. Additionally, the image colors produced by the flow model sometimes are rather soft or have less variation, which is indeed quite a big flaw for the electronic component images. However, in the long run, if in the future the industrial production line has strict requirements on both generation fidelity and output efficiency at the same time, Flow Matching is very likely to become a feasible middle way. On the one hand by virtue of the excellent performance of the diffusion model in high-fidelity synthesis, on the other hand retaining the inherent advantage of the flow model itself with fast inference speed, finally an actual balance can be found.

## 5. The comparative analysis and discussion

Table 1. Comparison of GAN, diffusion, and flow models in electronic component data augmentation

| Dimension | GAN | Diffusion Model | Flow Model |
|---|---|---|---|
| Generation Speed | Fast (single forward pass) | Slow (hundreds of denoising steps) | Moderate to fast (single pass for modern variants) |
| Image Quality | Good; may exhibit artifacts at edges | Excellent; fine detail preservation | Good; competitive with recent architectures |
| Training Stability | Unstable; prone to mode collapse and oscillation | Stable; straightforward noise prediction objective | Stable; maximum likelihood training |
| Computational Cost | Moderate (training); Low (inference) | High (both training and inference) | Moderate (both training and inference) |

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Table 1. (continued)

| | | | |
|---|---|---|---|
| Color | Strong color generation | Excellent texture and color fidelity | May produce muted colors |
| Electronic Component Applications | Relatively mature(PCB and IC) | Rapid developing(PCB) | Early stage; primarily anomaly detection |
| Best-Suited Scenario | Rapid sample expansion | High-fidelity defect synthesis | Structure-preserving generation |

Table 1 is used to carry out a multi - dimensional comparison among GAN, diffusion, and flow models in respect of electronic component data augmentation. Each of these three methods which have complementary advantages is the one that accords with different needs for generating electronic component samples. In terms of generation speed and image quality, diffusion models have always shown themselves to be more superior, which indeed highlights the significance of them in generating high-quality defective images. However, generating such high-quality samples has to go through repeated improvements, which will greatly prolong the generation time. On the contrary, the GAN model, in order to be able to generate quickly in a single step, has made a slight trade-off in the precision of details, thus not having such a high precision of details then. Process models, particularly that kind of process matching variant, strike a balance between the two, maintaining a relatively rapid generation speed while ensuring good image quality. This makes them especially advantageous in the field of electronic component manufacturing where both quality and real-time performance are vital.

Regarding the application of these methods to electronic components, each maturity level is quite different. GAN has amassed a great deal of rich experience in the field of printed circuit board components and also demonstrates very high practical value in semiconductor defect detection and industrial defect synthesis, so it is especially suitable for batch-generating defect samples. The diffusion model is developing rapidly in the field of electronic component enhancement, and it is shown in research that the enhancement method based on diffusion performs better than the best generative adversarial network (GAN) method in the multi - category printed circuit board inspection task. At present there is relatively little research about the electronic component enhanced flow model and the existing work mainly focuses on anomaly detection instead of sample generation however the potential of the flow model method should not be underestimated because modern variants have made great progress in generation quality and have shown great potential in this field.

There are still some limitations in the data augmentation of electronic components. The existing research has insufficient exploration of the flow model. Although the progress in the generation quality of modern variants demonstrates their great potential in the field of electronic component augmentation, the scarcity of application research gives the false impression that the flow model is inferior to GAN or diffusion models in this field. Moreover, most of the existing studies evaluate a single generation model separately. Rigorous research comparing the three methods under the same electronic component dataset is conspicuously lacking. Such comparative studies will provide practical guidance for method selection in the industrial field.

In the days to come the multi - model fusion strategy does have a considerable amount of exploration value. The hybrid architectures that can make use of the structural accuracy of flow models are able to guide the denoising path of diffusion models. Specifically, in each step of the reverse diffusion operation, the flow model is able to evaluate the log likelihood of the intermediate generated results. If the structural features do not match the geometric distribution of electronic components, the gradient of the flow model can immediately correct the denoising direction. This

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potential density guiding mechanism can effectively combine the texture fidelity advantage of the diffusion model and the geometric precision advantage of the flow model together. The development of lightweight models is another key direction. For example, techniques such as knowledge distillation and quantization, which can reduce the computational cost of generative models while not affecting the generation quality, are examples. For the purpose of adapting diffusion models and flow models to computing environments with limited resources, this is indeed especially necessary.

## 6. Conclusion

This paper conducts a systematic review of three generative models for electronic component image data augmentation: GANs, diffusion models, and flow-based models. It presents the theoretical bases of each method and their applications in electronic component detection. Analysis shows that these three generations of models have complementary characteristics and are suitable for different enhancement requirements. GAN that has an extremely fast generation speed and has been widely used in electronic component scenarios still has mode collapse and structural distortion as persistent problems. Among the three methods the diffusion model shows the highest generation quality however the main obstacle to their widespread application in the industrial field is the computational cost associated with iterative sampling although the research on inference acceleration methods is reducing this gap. The flow model that has unique advantages because of precise density estimation and reversible generation. Although at present they account for a small proportion in the current enhancement of electronic components, their solid theoretical foundations and recent progress in generation quality make them promising directions for future research. Comparative analysis shows that there are still some gaps in the current research field, for example, there is insufficient comparison of multiple models and insufficient exploration of methods based on flows. In future research, the concept of multi - model integration should be prioritized, the complementary advantages of different generation models should be combined, and a lightweight architecture design suitable for industrial deployment should be developed so as to better serve the industrial application of electronic component defect detection.

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