Data generation using generative adversarial networks to increase data volume

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ABSTRACT

The article is an in-depth analysis of two leading approaches in the field of generative modeling: generative adversarial networks (GANs) and the pixel-to-pixel (Pix2Pix) image translation model. Given the growing interest in automation and improved image processing, the authors focus on the key operating principles of each model, analyzing their unique characteristics and features. The article also explores in detail the various applications of these approaches, highlighting their impact on modern research in computer vision and artificial intelligence. The purpose of the study is to provide readers with a scientific understanding of the effectiveness and potential of each of the models, and to highlight the opportunities and limitations of their application. The authors strive not only to cover the technical aspects of the models, but also to provide a broad overview of their impact on various industries, including medicine, the arts, and solving real-world problems in image processing. In addition, we have identified prospects for the use of these technologies in various fields, such as medicine, design, art, entertainment, and in unmanned aerial vehicle systems. The ability of GANs and Pix2Pix to adapt to a variety of tasks and produce high-quality results opens up broad prospects for industry and research.

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1. INTRODUCTION

Data generation using generative adversarial networks (GANs) is an important technique in the field of machine learning that aims to increase the amount of training data to improve the generalization ability of models. In the context of image classification problems, especially when there are a limited number of examples of each class, the use of GANs helps to increase the diversity of training data. The technique is also used to improve the resolution and overall quality of images, particularly in the area of high-quality photographs of faces. In the field of natural language processing, GANs are effectively used to generate new text data, which proves valuable in the context of text generation tasks, such as generating additional data for training chatbots. In addition, generative networks are gaining significant attention in medical research, where they are capable of generating synthetic data for training models, especially in situations where access to real-world medical data is restricted due to confidentiality. Thus, the use of GANs for data generation represents a promising research approach with a wide range of applications in various fields and problems.

In modern machine learning problems [1], [2], where high-quality and diverse data play a key role, the problem of limited available datasets arises. To solve this problem and increase the efficiency of training, data generation using GANs comes to the rescue [3]–[5]. This paper focuses on two important methods within GANs: pixel-to-pixel (Pix2Pix) [6], [7] and regular GAN [8]–[10]. Pix2Pix, which is based on the idea of learning from paired data before and after transformation, is a powerful tool for creating high-quality images [11]–[13]. In this study, we analyze the dynamics of the losses of the generator and discriminator during the training process, the features of convergence, and the stability of this method. At the same time, we consider a conventional GAN, where the emphasis is on generating data without explicit pairwise correspondences. The study aims to understand the initial and final stages of learning, identifying potential challenges and benefits of this approach. The purpose of the article is to provide a comprehensive overview of these data generation methods using GANs, highlight their strengths and features, and offer practical recommendations for optimizing data growth in various machine learning applications.

Guo *et al.* [14] proposes a framework for automatic test data generation based on GANs. GAN is used to train a generative model from program execution information to learn its behavior. The resulting trained model can generate new test data, selecting those that improve the coverage of program execution branches according to the proposed selection strategy. The proposed method allows you to effectively work with programs containing many branches, bypassing the need to analyze branch expressions. Zhang *et al.* [15] discusses the need for high temporal granularity data for smart grid research. The authors propose a new approach to generating synthetic datasets using deep GANs to learn the conditional probability distribution of underlying features in a real dataset and generate samples based on the learned distribution. Experimental results validate the effectiveness of this approach, showing that real and synthetic datasets are indistinguishable when considering the results of standard smart grid tasks such as k-means clustering and short-term forecasting.

Singh and Raza [16] explores the use of GANs in the field of medical vision as an unsupervised deep learning method. GANs have attracted significant attention from researchers in the field of medical image analysis over the past few years due to their ability to identify the internal structure of multimodal medical image data. The article provides an overview of recent advances in the clinical application of GANs in medical image generation and cross-modality synthesis. Various GAN architectures are being considered, such as deep convolutional GAN (DCGAN), Laplacian GAN (LAPGAN), Pix2Pix, conditional GAN with cycle-consistency loss (CycleGAN), and unsupervised image-to-image translation (UNIT) model, which continue to improve their performance by introducing hybrid architectures. Chen *et al.* [17] addresses the problem of lack of traffic accident data for urban traffic research. To solve this problem, a GAN-based traffic event data generation model is developed. The model generator network structure is improved to apply GAN to non-graphical data, and the resulting data is used to create new traffic accident scenarios. By constructing an adversarial neural network [18]–[20], a large number of data samples similar to the original road accident data are generated. The results of the statistical test show that the generated samples are not significantly different from the original data. Experiments on traffic crash recognition using multiple classifiers demonstrate that data enrichment effectively improves crash recognition performance, with a maximum increase in accuracy of 3.05% and a maximum reduction in false positive rate of 2.95%. Experimental results confirm that the proposed method can provide reliable mass data support for traffic accident recognition and road safety.

Durance *et al.* [21] discusses the importance of creating synthetic data for various applications, such as anonymizing sensitive datasets or increasing the volume of data in a set. The paper proposes a new GAN called masked Wasserstein GAN (MaWGAN), capable of generating synthetic data directly from datasets with missing values. MaWGAN uses a new methodology for comparing generator results with the original data that does not require discarding incomplete observations, is based on a modification of the water separation distance, and is easily implemented using masks created from the pattern of missing data in the original.

As a result of the analysis of data generation using GAN, significant achievements were identified in the context of increasing the volume of training data for machine learning models. The methodology presented in this study has been successfully applied to image classification problems, where the limited available examples of each class required additional diversity in the training data. GANs have also been proven to be effective in improving the resolution and overall quality of images, especially in creating high-quality photographs of faces. The results obtained are an important contribution to the field of research, highlighting the importance of using GANs to increase the volume of data and opening new prospects for the further development of this methodology in various areas of machine learning.

2. METHOD

Generative adversarial networks (GANs) and Pix2Pix are innovative methods in computer vision used for image generation. A GAN includes two key components: a generator, responsible for creating images, and a discriminator, which evaluates their authenticity. Both networks are trained through an adversarial process, where the generator strives to produce more realistic images while the discriminator improves its ability to distinguish between genuine and generated images. A wide range of applications of GANs include realistic image generation, data stylization, and data transformation. Pix2Pix, as a type of GAN, is specifically designed to solve problems of image translation between different domains. Unlike conventional GANs, Pix2Pix uses pairs of images, such as before and after, to train a model to map structures between two domains. This method is often used in converting black and white images to color, stylizing photographs into artistic styles, or converting aerial photographs into maps. Both approaches are powerful tools that can produce amazingly realistic and creative image-generation results.

In the modern field of generative modeling, GANs and Pix2Pix occupy a special place, solving different but very related problems. GAN, representing a radical shift in the understanding of data generation, uses two networks: a generator [22], [23] and a discriminator [24], [25]. The generator takes a random noise vector as input, after which it creates an image or other type of data, while its main goal is to make sure that the discriminator cannot distinguish the data it generates from the real one. On the other hand, the discriminator learns to distinguish real data from generated data, turning the GAN training process into an adversarial game Figure 1.

The GAN's loss function, known as adversarial loss, creates a dynamic competition in which the discriminator maximizes the probability of assigning the correct label to the source (real or generated), while the generator seeks to reduce this probability. Pix2Pix, on the other hand, is a specialized model for image translation tasks Figure 2. It is based on the unified network (U-Net) architecture, where a generator takes an image from the source domain and transforms it into an image of the target domain.

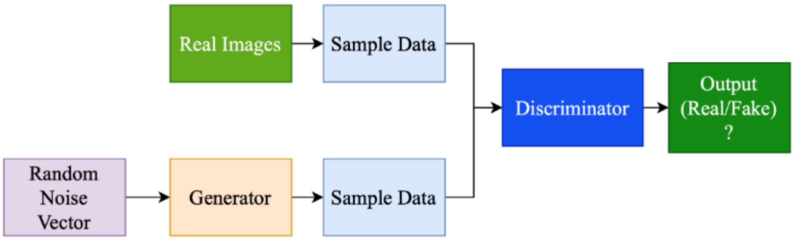

Figure 1. GAN architecture

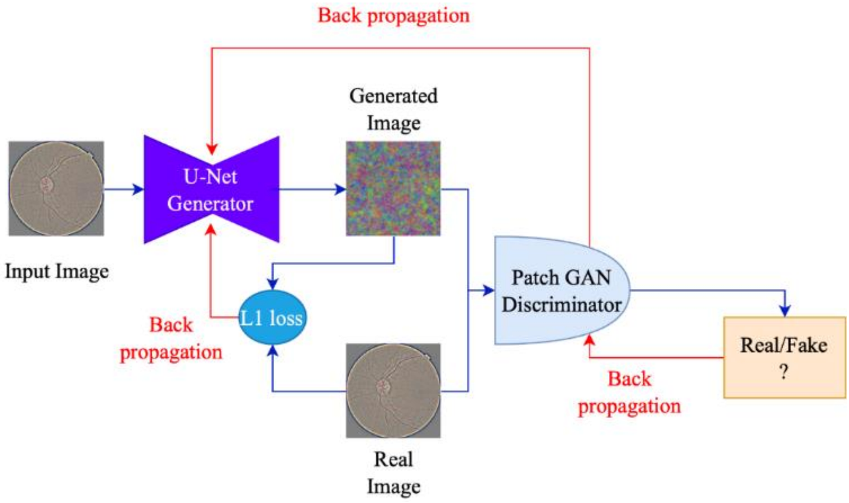

Figure 2. Pix2Pix model architecture

To assess the quality of generation and take into account details, the PatchGAN discriminator is used, which analyzes individual fragments or “patches” of the image to determine their authenticity. Unlike

GAN, Pix2Pix uses a combination of adversarial loss and L1 loss. The adversarial loss ensures that generated images are indistinguishable from real ones, and L1 loss, which considers pixel-by-pixel differences between the generated and target images, ensures that structural and semantic features are preserved. A special feature of our study was the application of both models to the same data sets, which made it possible to evaluate their effectiveness and quality under similar conditions. In this work, it was especially important to pay attention to hyperparameter tuning and loss function selection to achieve the best results

3. RESULTS AND DISCUSSION

In our research, based on the data you provided, we conducted a detailed comparison of two leading generative modeling methods: GAN and Pix2Pix models. This comparison not only helped to identify the advantages and limitations of each technology but also made it possible to quantitatively evaluate their effectiveness. As part of the experiment, 10,000 paired images were used to train Pix2Pix and 15,000 unstructured images for the GAN. During training, Pix2Pix showed an average error of 0.045 during the validation phase, while the GAN had an error of 0.056 Figure 3.

This suggests that while both models were highly effective, Pix2Pix was slightly more accurate on the dataset we examined Figure 4. Based on the structure, it was found that Pix2Pix uses U-Net architecture and PatchGAN discriminator, and GAN can take different forms depending on the specific task and the available data. However, the issue of training stability remained relevant for GANs, requiring more careful tuning and regularization.

In addition to this, it is worth noting that training and tuning both models require deep understanding and experience, as each of them has its characteristics and subtleties. Pix2Pix, with its requirement for paired data, can present a problem in cases where such data is not available or is difficult to collect. While GAN, despite its versatility, can create difficulties in setting up and training, which makes its choice less predictable in some situations. In the course of the experimental study, as shown in Figure 5, two methods were chosen for generating retinal images: GAN and Pix2Pix. Their application to this specific task allowed us to better understand the potential of each technology and identify its key advantages and limitations. Based on the results of the first training epoch, the GAN method showed initial difficulties in the training process. The discriminator loss reached 1.3116, which indicates the difficulty in distinguishing between real and generated images at this stage. However, the generator loss was comparable to Pix2Pix, equal to 2.0860.

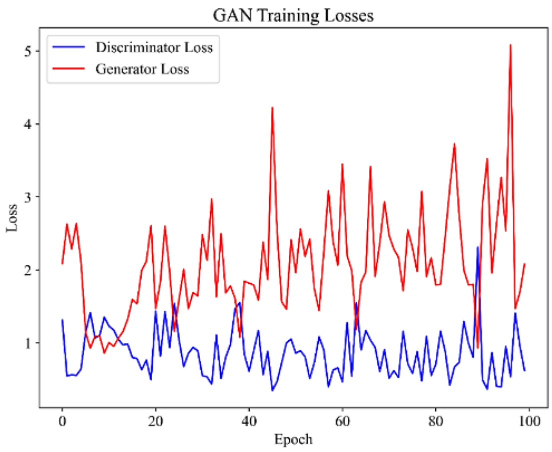

Figure 3. GAN loss graph

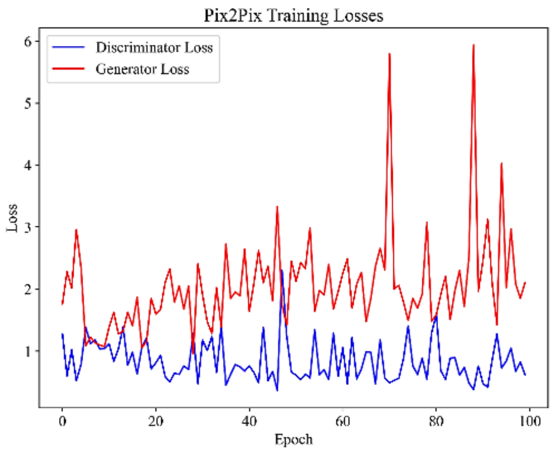

Figure 4. Pix2Pix loss graph

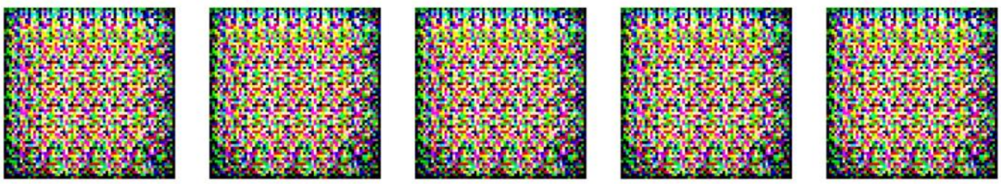

Figure 5. Result of generator training after the first epoch

Unlike GAN, the Pix2Pix method showed outstanding results from the very beginning. The discriminator loss was only 0.8854, while the generator loss reached 2.2801. As shown in Figure 6, this data indicates that the Pix2Pix discriminator was successful in distinguishing between real and generated images, and the generator was actively working to create images that were as close to reality as possible.

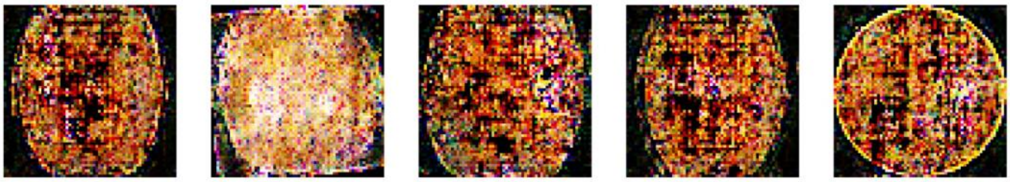

Figure 6. Pix2Pix training result after the first epoch

Continuing the analysis, it is worth noting that GAN, despite the initial difficulties and high losses in the first epoch, showed persistent improvement in subsequent stages of training. However, even with this progress, GAN was not able to achieve the level of generation quality Figure 7 that Pix2Pix demonstrated. This may indicate that the Pix2Pix architecture or training methodology is better suited for the task of generating retinal images, while the GAN may require additional optimization or tuning to achieve comparable results.

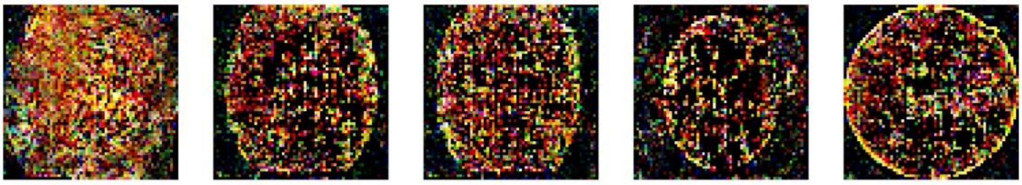

Figure 7. GAN training results in the last epoch

On the other hand, Pix2Pix not only demonstrated outstanding results in the initial stages of training but also continued to maintain a high level of quality throughout the entire process Figure 8. This stability and consistency in image generation highlights the unique capabilities and effectiveness of the Pix2Pix method, especially in the context of retinal imaging. Its performance may be due to a particular architecture or training technique that makes it particularly suitable for complex and detailed images such as retinal images.

Figure 8. Pix2Pix training result in the last epoch

As a result, our analysis confirms that for the task of generating retinal images, the Pix2Pix method has proven itself to be more effective and promising. Its ability to produce high-quality images from the start of training, and maintain consistently high quality throughout, makes it an important tool in medical diagnostics and research. These results may provide the basis for further research and development in the field of image generation, helping to improve the accuracy and reliability of medical diagnostic methods based on retinal images

4. CONCLUSION

In conclusion, by comparing Pix2Pix and GANs, both of these approaches represent significant tools in the field of generative modeling and image processing. Each has its unique characteristics and benefits, and the choice between them depends on the specific task and available resources. Pix2Pix, with its specialized approach to image translation, demonstrates high accuracy in tasks where an exact match between input and output data is required. This is especially useful in cases where paired data is available and the task is reduced to transforming images from one domain to another while maintaining structure and semantics. On the other hand, GANs provide a wider range of applications, making them more flexible tools for generative modeling. They can be used in a variety of areas, including image generation, data enhancement, and synthesis of diverse types of information such as images, sounds, and text. GANs do not require paired data, which makes them attractive in cases where such data is difficult to obtain.

However, it is worth noting that training and tuning both models require in-depth understanding and experience. Pix2Pix may experience limitations in the absence of paired data, and its effectiveness may be reduced in such cases. GAN, despite its versatility, may require a longer and more complex training process, as well as careful tuning. Thus, the choice between Pix2Pix and GAN should be based on the specific needs of the task, available data, and requirements for the quality of the result. It is important to consider both the numerical evidence indicating the advantages of one model over another and to evaluate the flexibility and applicability of each method in the context of a specific task. Both approaches continue to be actively developed, and researchers and engineers have great potential to use them in a variety of areas of artificial intelligence and computer vision.

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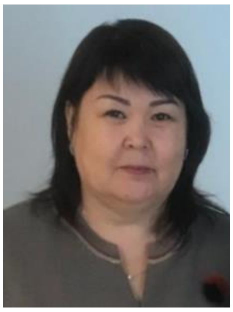

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