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Generative Adversarial Network (GANs) for Image Generation or Data Augmentation

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Abstract

In recent years, image segmentation has become a crucial aspect in various fields, ranging from disease diagnosis to autonomous vehicle navigation. In computer vision, image segmentation is a vital task and is more complex than other vision problems due to its reliance on low-level spatial data. Deep Learning has significantly influenced the field of segmentation, resulting in several successful models today. Among these, Generative Adversarial Networks (GANs) have shown remarkable performance in image segmentation. This study provides a systematic review of recent publications on GAN models and their applications. The authors conducted a search across three databases—Embase (Scopus), WoS, and PubMed—to find relevant papers, resulting in 2,084 documents. After a two-phase screening process, 52 records were selected for the final review. Key applications of GANs identified include 3D object generation, medicine, pandemics, image processing, face detection, texture transfer, and traffic control. Prior to 2016, research in this area was limited, but its practical application has grown significantly worldwide since then. The study also highlights the challenges associated with GANs and suggests directions for future research in this field. In this paper, we introduce an adversarial approach for abstractive text summarization, where we concurrently train a generative model (G) and a discriminative model (D). Specifically, the generator G is designed as a reinforcement learning agent that takes raw text as input and produces an abstractive summary. The discriminator, on the other hand, attempts to differentiate the generated summary from the ground truth summary. Extensive experiments show that our model achieves competitive ROUGE scores compared to state-of-the-art methods on the CNN/Daily Mail dataset. Additionally, qualitative results demonstrate that our model generates summaries that are more abstractive, readable, and diverse. Generative Adversarial Networks (GANs) are a type of artificial intelligence algorithm developed to address the generative modelling problem. The objective of a generative model is to analyse a set of training examples and learn the underlying probability distribution that generated them. GANs then use this estimated distribution to generate new examples. While deep learning-based generative models are common, GANs stand out as one of the most successful, particularly due to their ability to produce realistic high-resolution images. GANs have been applied successfully to a wide range of tasks, primarily in research contexts. However, they continue to present unique challenges and research opportunities, as they are grounded in game theory, unlike most other generative modelling approaches that rely on optimization techniques. Deep learning has made significant advancements in the field of artificial intelligence, leading to the development of various deep learning models. One such model, Generative Adversarial Networks (GANs), was introduced based on zero-sum game theory and has quickly become a prominent research focus. The importance of GANs lies in their ability to learn data distributions through unsupervised learning and generate more realistic, authentic data. Due to their vast application potential, including in image and vision computing, as well as video and language processing, GANs have been widely studied. This paper provides an overview of GANs, including their theoretical foundations and various extensions that enhance or modify the original model's structure. The paper also explores typical applications of GANs, outlines existing challenges, and discusses future directions for GAN model development.

Keywords: GANs, Image Generation, Data Augmentation, Deep Learning, Systematic Review

Introduction

Research in Generative Adversarial Networks (GANs) has seen rapid growth in recent years. Since its introduction in 2014, GANs have been applied to various fields such as computer vision and natural language processing, achieving remarkable results. Among the numerous applications of GANs, image synthesis stands out as the most extensively studied, with research in this area showcasing the significant potential of GANs for image generation. This paper presents a taxonomy of methods used in image synthesis, reviews different models for text-to-image synthesis and image-to-image translation, and explores evaluation metrics and potential future research directions in GAN-based image synthesis. We introduce and emphasize generative modelling as a key task in machine learning, offering a critical perspective on the algorithms developed to address this challenge. We explain how generative modelling can be mathematically defined as the process of aligning an estimated distribution with an unknown true distribution, which can be measured using statistical divergence between the two. We discuss the maximum likelihood approach and how it can be understood as minimizing KL-divergence. We examine several methods within the maximum likelihood framework, highlighting their limitations. Next, we delve into the alternative adversarial approach, which focuses on comparing the differences between an estimated distribution and the real data distribution. We explain how this approach leads to the development of new divergences and techniques necessary for successful adversarial learning. Finally, we discuss the new evaluation metrics that are required for this adversarial approach. Generative adversarial networks (GANs) are a deep learning-based approach to generative modelling that incorporate strategies like Convolutional Neural Networks (CNNs). In deep learning, generative modelling is an unsupervised learning task focused on identifying and understanding the general patterns or structures within input data, enabling the model to generate new instances that resemble the original data. GAN models are currently used to generate images from text, create videos from static images, enhance image resolution, and transform images. Their applications span from anomaly detection to improvements in chess games. Recent advances in GANs have led to the creation of hyper-realistic human face images, often referred to as "Deepfakes," which are nearly indistinguishable from real photographs to the human eye. The manipulation of these images online raises significant ethical, moral, and legal concerns. As new GANs continue to emerge rapidly, one important area of research is developing forensic models capable of detecting new GAN-generated images. The forensics community is exploring innovative methods to detect fake images, especially facial forgeries, and ensure the integrity of visual content. It is clear that the field of deep learning is becoming increasingly focused on GANs, given their wide range of applications.

Literature Review

Saxena, D., Et al (2021) Generative Adversarial Networks (GANs) are a novel class of deep generative models that have recently attracted significant attention. GANs are capable of learning complex, high-dimensional distributions across images, audio, and data. However, training GANs presents several challenges, such as mode collapse, non-convergence, and instability, often arising from issues in network architecture design, objective functions, and optimization algorithm selection. Recently, various solutions have been proposed to address these challenges, focusing on re-engineered network architectures, new objective functions, and alternative optimization algorithms. To the best of our knowledge, there has been no comprehensive survey dedicated specifically to the broad and systematic development of these solutions. In this study, we provide an extensive survey of advancements in GAN design and optimization strategies aimed at overcoming these challenges. We first identify key research issues within each design and optimization approach, then propose a new taxonomy to categorize the solutions by these key issues. Following the taxonomy, we offer a detailed discussion of different GAN variants within each solution and their interrelationships. Finally, based on the insights gathered, we outline promising research directions in this rapidly evolving field. [1]

Cao, Y, J., Jia, L. L., Chen, Y. X., Lin, N., Yang, C., Zhang, B., ... Et al (2018) The emergence of Generative Adversarial Networks (GANs) has introduced a new approach and framework for computer vision. Unlike traditional machine learning algorithms, GANs leverage an adversarial training concept, which enhances their ability to learn features and representations more effectively. However, GANs also face challenges such as non-convergence, model collapse, and uncontrollability due to their high degree of freedom. Addressing these issues and applying GANs to computer vision tasks has become a major area of research. This paper provides a comprehensive review of recent GAN models and their applications in computer vision. Specifically, we begin by surveying the history and evolution of generative algorithms, the mechanism behind GANs, their foundational network structures, and a theoretical analysis of the original GAN. We then compare classical GAN algorithms in terms of their mechanisms, visual quality of generated samples, and Fréchet Inception Distance (FID). These networks are further evaluated through extensive experiments on public datasets, considering factors such as network construction, performance, and applicability. Additionally, the paper explores several key applications of GANs in computer vision, including high-quality sample generation, style transfer, and image translation. Finally, we summarize the existing challenges in GANs and discuss potential future research directions.[2]

Chen, Y., Yang, X, H., a, A., Zheng, N., Li, Z., ...Et al (2022) Affine transformations, such as flipping and scaling, are among the most common image augmentation techniques. While these methods can significantly increase the number of samples, the new images often remain too similar to the original ones, resulting in only a slight improvement in dataset diversity. Image stitching is another traditional augmentation technique, which combines the foreground and background regions of different images in a copy-paste fashion. While this approach can enhance sample diversity to some extent, it may not be suitable for medical images with complex textures, as the samples generated may fail to meet clinical characterization standards. To address this issue, researchers have begun exploring augmentation models based on machine learning. These models, often referred to as image "fakers," learn the common features across a dataset and then generate new samples by imitating or transforming existing images. Among these models, Generative Adversarial Networks (GANs) have gained significant attention due to their impressive image generation capabilities and have been widely applied in medical image augmentation. Therefore, a systematic review of existing GAN-based methods for medical image augmentation is warranted. A GAN consists of a generator (the "faker") and a discriminator.

The discriminator is tasked with accurately classifying images as real or fake, while the generator aims to create images so realistic that the discriminator cannot easily distinguish them. The two components are trained iteratively, with the performance of both improving alternately. Through this adversarial training process, the generator's performance is significantly enhanced. GANs thus provide essential constraints on the generator's training, and since there are no specific structural requirements for the generator, GAN-based medical image augmentation methods hold significant research value. According to the Engineering Village (EI) search results, the first EI-indexed study on using GANs for medical image dataset augmentation was published in 2018. This paper reviews 105 research works on GAN-based medical image augmentation published or pre-published in ELSEVIER, IEEE Xplore, and Springer between January 1, 2018, and December 31, 2021. These papers are categorized into ten topics based on human organ parts, including the brain, fundus, chest and lung, breast, heart, abdomen, skin, microscopically stained samples, other organs or parts, and multiple organs and parts. In each topic, we organize essential details such as datasets, benchmark models, loss functions, and downstream applications discussed in the literature. Additionally, we conducted an overview analysis of the papers published in three key journals and three prominent conferences in the field of medical image processing. The journals include IEEE Transactions on Medical Imaging, Medical Image Analysis, and Computers in Biology and Medicine, while the conferences are Medical Image Computing and Computer Assisted Intervention, Information Processing in Medical Imaging, and International Symposium on Biomedical Imaging. The distribution of the reviewed papers is presented in the following statistics.[3]

Alqahtani, H., Kavali Throne, M., Et al (2021) Generative Adversarial Networks (GANs) provide a method for learning deep representations without the need for heavily annotated training data. These networks achieve learning by generating backpropagation signals through a competitive process involving two networks. The representations learned by GANs can be applied to various domains. GANs have seen significant progress and outstanding performance across numerous applications, including semantic image editing, style transfer, image synthesis, image super-resolution, and classification. This paper aims to offer an overview of GANs, their different variants, and their potential applications in various fields. It highlights the advantages, disadvantages, and key challenges associated with successfully implementing GANs in different application areas. The primary goal of this paper is to provide a comprehensive review of the major applications of GANs, examining the techniques and architectures used, as well as the contributions of these applications to real-world scenarios. The paper concludes with a discussion on future directions and prospects for GANs. [4]

Wang, X., Wang, K., Et al (2020) The quality and size of the training set significantly influence the outcomes of deep learning-based face-related tasks. However, collecting and labelling sufficient high-quality samples with balanced distributions remains a labour-intensive and costly process, leading to the widespread use of various data augmentation techniques to enhance the training dataset. This paper reviews existing face data augmentation methods, focusing on the types of transformations and techniques used, with an emphasis on state-of-the-art approaches. Among these methods, we highlight deep learning-based techniques, particularly Generative Adversarial Networks (GANs), which have emerged as powerful and effective tools in recent years. We explain the principles behind these methods, discuss their results, and explore their applications and limitations. Additionally, we introduce different evaluation metrics used to assess these approaches. Finally, we address the challenges and opportunities in the field of face data augmentation and provide concise yet insightful discussions.[5]

Ur Rahman, z., Asaari, M, S, M., lbrahim, H., Abidin, l, S, Z., Et al (2024) Enhancing model performance in agricultural image analysis is challenging due to factors such as limited datasets, biological variability, and unpredictable environments. Deep learning models typically require large, realistic datasets, which are often difficult to gather. Data augmentation, particularly using Generative Adversarial Networks (GANs), has become a vital tool in agricultural applications by generating synthetic images that help improve model training and minimize the need for extensive image collection. This review examines various GAN-based image augmentation techniques in agriculture, exploring their challenges and limitations. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, 128 publications were analysed to identify emerging trends and research gaps in GAN applications within agriculture. Key applications of GANs include plant classification, weed detection, animal detection and behaviour recognition, animal health and disease analysis, plant disease detection, phenotyping, and fruit quality assessment. Ongoing challenges such as limited training datasets, occlusion issues, and imbalanced data continue to affect model performance in these areas. Addressing these challenges is crucial for improving the efficiency and effectiveness of agricultural operations. The review concludes with insights and future directions to promote further advancements in this field. [6]

Biswas, A., Md Abdullah Al, N., Imran, a., Sejuty, fairooz, F., Puppala (2023) One approach to expanding the dataset for training AI models in the medical field is through data augmentation using Generative Adversarial Networks (GANs). GANs consist of two networks: a generator that creates new data samples, and a discriminator that evaluates their similarity to real data. The discriminator is trained to distinguish between real and synthetic samples, while the generator is trained to produce data that closely resembles actual data. This process is repeated until the generator generates synthetic data that is indistinguishable from real data. GANs have been applied in medical image analysis for various purposes, including data augmentation, image generation, and domain adaptation. They can create synthetic samples to enhance the available dataset, particularly when obtaining large amounts of real data is challenging or unethical. However, it's important to note that the use of GANs in medical imaging remains an evolving field of research, aimed at ensuring the quality and clinical applicability of the generated images.[7]

Panday, S., Singh, P. R., Et al (2020) A key challenge in applying deep neural network techniques to medical imaging is addressing small datasets and the scarcity of annotated samples. To overcome this, data augmentation methods, such as traditional geometric transformations and more recent image synthesis techniques using Generative Adversarial Networks (GANs), can be used to artificially increase the number of training images. This paper focuses on data augmentation for image segmentation, which presents a unique challenge compared to conventional image classification, as it requires generating a corresponding mask for each image. To address the challenge of augmenting image-mask pairs for segmentation, this paper introduces a novel two-stage GAN approach. In this approach, the first GAN generates a synthetic binary mask, which is then used by the second GAN to conditionally generate the corresponding image. These two GANs work together to produce synthesized image-mask pairs that can enhance the performance of traditional image segmentation methods. The proposed method is evaluated on the task of cell nuclei image segmentation and shows superior performance, outperforming both traditional augmentation techniques and existing GAN-based augmentation methods in extensive tests conducted on the benchmark Kaggle cell nuclei image segmentation dataset.[8]

Peraz, J., Arroba, P., Et al (2023) The Cloud computing paradigm is at a critical juncture, where existing energy-efficiency techniques are reaching their limits, while the demand for computing resources in Data Centre facilities continues to grow exponentially. One of the main challenges in creating a global energy efficiency strategy using Artificial Intelligence is the need for large amounts of data to feed the algorithms. This paper introduces a time-series data augmentation approach based on synthetic scenario forecasting within Data Centers. To achieve this, we employ a powerful generative algorithm: Generative Adversarial Networks

(GANs). Specifically, our work integrates GAN-based data augmentation with scenario forecasting, addressing the gap in synthetic data generation for Data Centers. Additionally, we propose a methodology to enhance the variability and heterogeneity of the generated data by introducing on-demand anomalies, without requiring extra effort or expert knowledge. We also introduce Kullback-Leibler Divergence and Mean Squared Error as new metrics for validating synthetic time series generation, as they offer a more comprehensive comparison of multivariate data distributions. Our approach is validated using real-world data collected from an operational Data Centre, successfully generating synthetic data that supports prediction and optimization models. Our research aims to optimize energy consumption in Data Centers, though the proposed methodology can also be applied to other time-series-related problems. [9]

Kusiak, A. (2020) Manufacturing is undergoing a transformation driven by advancements in process technology, information technology, and data science. The future of manufacturing will be highly digital, creating opportunities for machine learning algorithms to develop predictive models across the enterprise, aligned with the concept of the digital twin. Convolutional and Generative Adversarial Networks (GANs) have gained attention within the manufacturing research community. This paper presents key research and applications of these two machine learning techniques in manufacturing, discussing their respective advantages and limitations. The paper aims to identify research gaps, inspire machine learning research in emerging manufacturing domains, contribute to the development of effective neural network architectures, and provide deeper insights into manufacturing data.[10]

Branikas, E., Murray, P., Et al (2023) Condition monitoring and inspection are essential for evaluating the health of critical infrastructure, ranging from road networks to nuclear power plants. Defect detection through visual inspections of these assets has been gaining increasing attention. However, data-based models often face challenges due to the limited availability of data representing cracks in various forms, leading to significant data imbalance. This paper introduces a novel data augmentation technique using the Cycle GAN Generative Adversarial Network (GAN). The proposed model is applied to different image datasets depicting cracks, with a focus on a nuclear application as the primary industrial example. The goal of the network is to enhance segmentation accuracy on these datasets through deep convolutional neural networks. The GAN generates realistic images that are difficult to segment and under-represented in the original datasets. Various deep networks are trained on the augmented datasets, without adding any labelling overhead. A comparison is made between the performance of different neural networks on the original data and the augmented datasets. Extensive experiments show that the proposed augmentation method significantly improves crack detection in challenging cases across all datasets, as indicated by the increase in quantitative evaluation metrics. [11]

Vaccari, l., Orani, V., Paglialonga, A., Cambiaso, E., Et al (2021) The use of machine learning and artificial intelligence in the medical field is expanding, with applications ranging from disease identification and prediction to patient monitoring and clinical decision support systems. Additionally, the growing adoption of remote monitoring devices under the “Internet of Medical Things” (IoMT) has made it easier to collect patient data, enabling continuous monitoring and providing healthcare providers with direct access to real-time information. However, challenges such as connectivity issues, irregular usage, misuse, or poor adherence to monitoring programs may result in insufficient data for accurate algorithm development. To address this, data augmentation techniques can be employed to generate synthetic datasets large enough to train machine learning models effectively. In this study, we apply Generative Adversarial Networks (GANs) for data augmentation using patient data collected from IoMT sensors for monitoring Chronic Obstructive Pulmonary Disease (COPD). We also incorporate an explainable AI algorithm to verify the accuracy of the synthetic data by comparing it with real sensor data. The results demonstrate that synthetic datasets created with a well-structured GAN are comparable to real datasets, as validated by a novel machine learning-based approach. [12]

Li, X., Metsis, V., Wang, H., Et al (2022) Signal measurements in the form of time series are commonly used in medical machine learning applications. However, these datasets are often small, which can make training deep neural network architectures ineffective. For time-series data, the options for data augmentation are limited by the need to preserve the inherent properties of the signal. One potential solution is using data generated by a Generative Adversarial Network (GAN) as an augmentation tool. RNN-based GANs, however, struggle to effectively model long sequences with irregular temporal relationships. To address this challenge, we introduce TTS-GAN, a transformer-based GAN capable of generating realistic synthetic time-series data sequences of arbitrary length that closely resemble real data. Both the generator and discriminator networks in our GAN model are built using a pure transformer encoder architecture. We use visualizations and dimensionality reduction techniques to show the similarity between real and generated time-series data. Additionally, we compare the quality of our generated data with that of the best existing alternative, an RNN-based time-series GAN. [13]

Ferreira, A., Magalhaes, R., Et al (2022) Artificial intelligence is rapidly advancing, but techniques like deep learning require more data than is typically available, particularly in the medical field. Often, the existing datasets are not fully representative of real-world conditions, necessitating the acquisition of additional samples, which can be costly. As a result, there is an increasing demand for tools that can generate as much data as needed. Traditional data augmentation methods can expand existing datasets, but they cannot generate entirely new data. Generative adversarial networks (GANs) have proven to be transformative for big data by creating synthetic data and increasing the available dataset with minimal cost. In this context, an adaptation of alpha-GAN for 3D MRI scans was developed to create a pipeline for generating as many synthetic rat brain scans as required. The synthetic data's applicability was tested through a segmentation task, and its realism was assessed visually. [14]

Shao, S., Wang, P., Et al (2019) However, there has been limited research on generating raw sensor signal data. Additionally, most existing studies on GAN evaluation rely on visual assessment of sample quality, which is not suitable for sensor signal scenarios. Therefore, this paper represents a novel attempt to use the ACGAN architecture for generating mechanical sensor signals for data augmentation and subsequent fault classification. It also proposes a new evaluation system to assess the quality of the generated samples. The main contributions of this paper are as follows:

1. **Proposed ACGAN Architecture**: An ACGAN architecture using one-dimensional convolutional layers is introduced to learn features from limited training data and generate realistic sensor data. The high-quality samples produced can be used for further applications in machine fault diagnosis. A one-dimensional convolutional neural network (1D-CNN) is employed as the building block for both the generator and discriminator to take advantage of its ability to learn local and hierarchical representations from raw data. These features are beneficial for classification tasks and contribute to feature interpretability. Category labels are incorporated into both the generator and discriminator to expedite model training, and batch normalization is applied in the generator to address the vanishing gradient issue and prevent overfitting.
2. **Evaluation Metrics for Performance Assessment**: To evaluate the generative model's performance, a set of metrics is introduced to assess the quality of the generated samples both quantitatively and

visually. To analyse the diversity of the generated samples versus the true data, statistical characteristics in the time domain and frequency distribution are calculated. For classification performance, experiments using generated samples to train and test a classifier are conducted to verify the effectiveness of the synthetic data in fault diagnosis tasks.

3. **Experimental Results**: Experimental results using an induction motor dataset are presented, demonstrating the data generation capability of the proposed framework and providing classification results using the artificially augmented dataset. Various generator construction strategies are also investigated for comparison.

The remainder of the paper is structured as follows: Section II introduces the theoretical background on generative adversarial networks, training strategies, and the proposed evaluation method. Section III provides a detailed description of the entire ACGAN-based framework. Section IV presents experimental verification and a discussion of the results. Finally, Section V concludes the paper and outlines future research directions. [15]

Declaration of Conflicting Interests

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