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Exploring Generative Adversarial Networks (GANs) for Image Synthesis

Arshad Ali[1]

Senior Instructor Computer Science, Govt Graduate College of Commerce Sheikhupura. arshadalimcs@gmail.com

Khaliq Ahmed[2]

Computer Science Department, IQRA University, Karachi Pakistan khaliq@iqra.edu.pk

Muzammil Ahmad Khan[3]

Computer Engineering Department, Sir Syed University of Engineering and Technology, Karachi Pakistan muzammilahmad.khan@gmail.com

Muhammad Nadeem[4]

Department of Computer Science & Information Technology

Sir Syed University of Engineering and Technology, Karachi Pakistan.

mnadeem79@gmail.com

Hermain Fayyaz Karim[5]

Department of Computer Science, Nazeer Hussain University, Karachi Pakistan. hermain.fayyaz@nhu.edu.pk

Dr. Ghulam Mustafa[6]

Assistant Professor, Department of Information Technology

University of the Punjab. Gujranwala Campus.

Gmustafa@pugc.edu.pk

Abstract

Background: Generative Adversarial Networks (GANs) have revolutionized image synthesis by enabling the generation of highly realistic images.

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However, the effectiveness of GANs varies depending on architecture and training methodologies. This study evaluates the performance of a proposed GAN model compared to advanced architectures such as StyleGAN2 and BigGAN, using the CIFAR-10 dataset as a benchmark. Objective:The primary objective of this study is to assess the ability of GANs to generate high-quality, diverse images by comparing the proposed GAN model with established architectures. Performance is evaluated using key metrics such as the Inception Score (IS) and Fréchet Inception Distance (FID).Method:An experimental study design was employed, utilizing a GAN architecture comprising a generator and a discriminator trained in an adversarial manner. The CIFAR-10 dataset, consisting of 60,000 images across 10 categories, was used for training and evaluation. The Inception Score (IS) and Fréchet Inception Distance (FID) were calculated to assess image quality and diversity. Subjective visual assessments and computational efficiency were also analyzed.Results:The proposed GAN achieved an IS of 7.8 and an FID of 25.5, indicating moderate image quality and diversity. In comparison, StyleGAN2 and BigGAN outperformed the proposed model with IS scores of 8.3 and 8.7, and FID scores of 15.2 and 14.0, respectively. Despite its lower performance in image synthesis, the proposed GAN exhibited a significantly reduced training time (36 hours) compared to StyleGAN2 (72 hours) and BigGAN (96 hours). No significant mode collapse was observed across the models. However, subjective evaluations confirmed that the proposed GAN produced images of lower visual quality than its counterparts.Conclusion:While the proposed GAN demonstrated efficient training times, it lagged in terms of image quality and diversity compared to more advanced models. Future research should

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focus on optimizing training strategies and architectural improvements to enhance GAN performance while maintaining computational efficiency.

Keywords: Generative Adversarial Networks (GANs), Image Synthesis, Deep Learning, Inception Score (IS), Fréchet Inception Distance (FID)

Introduction

Generative Adversarial Networks (GANs), introduced by Ian Goodfellow and colleagues in 2014, have revolutionized the field of image synthesis[1]. A GAN consists of two neural networks, the generator and the discriminator, that are trained simultaneously through adversarial processes[2]. The generator aims to produce images indistinguishable from real ones, while the discriminator evaluates and distinguishes between real and generated images. This dynamic fosters the creation of highly realistic images[3].Over the past decade, GANs have undergone significant advancements, leading to the development of various architectures tailored for image synthesis. Notable among these are Conditional GANs (cGANs), which incorporate additional information to guide the image generation process, and CycleGANs, designed for image-to-image translation tasks without requiring paired datasets[4]. These innovations have broadened the applicability of GANs across diverse domains.The impact of GANs on image synthesis is profound, enabling applications such as image-to-image translation, where images are transformed from one domain to another (e.g., converting sketches to realistic images), and text-to-image generation, which creates images based on textual descriptions[5]. Furthermore, GANs have been instrumental in enhancing image resolution, style transfer, and even generating entirely new visual content, thereby pushing the boundaries of what is achievable in computer vision and

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graphics[6].Despite these advancements, challenges persist in training GANs, including issues related to stability, mode collapse, and the need for large datasets[7]. Ongoing research focuses on addressing these challenges through improved training techniques, architectural modifications, and the development of evaluation metrics to assess the quality and diversity of generated images[8].In summary, GANs have established themselves as a cornerstone in the field of image synthesis, continually evolving to overcome challenges and expand their capabilities. Their development has opened new avenues for research and applications, making them a focal point for ongoing studies in artificial intelligence and computer vision.

Literature Review

Alimisis P(2025):This comprehensive review delves into the advancements of GANs in image processing, emphasizing their impressive performance in various applications. The authors systematically categorize recent research, focusing on image generation, enhancement, and translation tasks. They also discuss the challenges associated with GAN training, such as stability issues and mode collapse, and explore potential solutions proposed in contemporary studies[9]. Granger E(2021):This review provides an in-depth analysis of GAN architectures employed in unsupervised learning, tracing their evolution.The paper highlights various GAN models, including Conditional GANs and CycleGANs, and their applications in tasks like text-to-image synthesis and image-to-image translation. The authors also examine the methodologies that enable GANs to convert textual descriptions into authentic images, underscoring the versatility of these networks[10].

Pande S(2021):This literature review offers a thorough examination of GAN

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models, discussing their foundational principles and the progression of their architectures. The authors explore various GAN variants, such as StackGAN and high-resolution image synthesis models, detailing their contributions to photorealistic image generation. The paper also addresses the challenges in training GANs and the strategies developed to overcome them, providing a holistic view of the field's advancements[11].

Hong S(2018):This survey presents an extensive overview of adversarial models for image synthesis, categorizing methods into image-to-image translation, fusion image generation, label-to-image mapping, and text-to-image translation. The authors review an extensive selection of previous works, discussing various GAN architectures, loss functions, evaluation metrics, and training datasets. The paper also provides insights into the development trajectory from model-based to data-driven methods and highlights potential future research directions[12]. Liang X(2017):This review explores the diverse applications of GANs across various sectors, including image processing, video generation, and prediction. The authors discuss how GANs combine two neural networks that compete against one another using zero-sum game theory, allowing them to create much crisper and discrete outputs. The paper also delves into the challenges and future prospects of GANs in these fields[13]. Newton D(2019):This systematic review focuses on the application of GANs in AI-generated artwork, analyzing various algorithms and their performance in image generation. The authors assess the quality of the generated images and discuss the advancements in GAN architectures that have contributed to improvements in artistic image synthesis. The paper also identifies current limitations and suggests areas for future research in AI-driven art creation[14].

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Alam M(2020):This survey examines the integration of Transformer networks into GAN architectures for computer vision applications. The authors discuss how Transformers, known for capturing global relationships in data, enhance GAN performance in image and video synthesis tasks. The paper provides a comparative analysis of Transformer-based GAN models, highlighting their advantages over traditional convolutional approaches and discussing potential future research directions[15]. Agnese J(2021):This survey provides a taxonomy of methods used in adversarial image synthesis, reviewing different models for text-to-image synthesis and image-to-image translation. The authors discuss various GAN architectures, their applications, and the evaluation metrics used to assess their performance. The paper also highlights the challenges in the field and proposes potential future research directions to address these issues[16]. Chan CS(2017):This review focuses on the impact of deep learning, particularly GANs, on image synthesis and editing techniques. The authors discuss how GANs have outperformed traditional methods in generating realistic images and explore various GAN architectures and their applications in image synthesis. The paper also addresses the challenges in training GANs and the strategies developed to overcome them, providing a comprehensive overview of the field[17].

Thies J(2019):This paper provides an overview of GANs with a special focus on algorithms and applications for visual synthesis. The authors cover several important techniques to stabilize GAN training and discuss applications in image translation, image processing, video synthesis, and neural rendering. The paper also highlights the challenges in GAN training

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and the strategies developed to address them, offering insights into the future directions of GAN research[18].

Material And Methods

Study Design

This research employs an experimental design to assess the effectiveness of GANs in generating realistic images. We implement a GAN architecture comprising a generator and a discriminator, trained in an adversarial manner. The generator aims to produce images that mimic real data, while the discriminator evaluates and distinguishes between real and generated images. This adversarial training process is iterative, with both networks improving their performance over time[19].

Data Collection

In our exploration of Generative Adversarial Networks (GANs) for image synthesis, we utilized the CIFAR-10 dataset, a widely recognized benchmark in machine learning and computer vision research. The CIFAR-10 dataset comprises 60,000 color images, each with dimensions of 32x32 pixels, categorized into 10 distinct classes: airplanes, automobiles, birds, cats, deer, dogs, frogs, horses, ships, and trucks. Each class contains 6,000 images, with the dataset partitioned into 50,000 training images and 10,000 test images. This structure ensures a balanced representation across classes, facilitating comprehensive training and evaluation of GAN models. The diversity and standardized format of CIFAR-10 make it an ideal choice for assessing the performance of image synthesis algorithms, providing a consistent framework for comparison across different studies.

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Study Population

The CIFAR-10 dataset is a widely utilized benchmark in machine learning and computer vision research, particularly in the evaluation of image synthesis models like Generative Adversarial Networks (GANs). Developed in 2009, it comprises 60,000 color images, each with dimensions of 32x32 pixels, systematically categorized into 10 distinct classes: airplanes, automobiles, birds, cats, deer, dogs, frogs, horses, ships, and trucks. Each class contains 6,000 images, providing a balanced representation across categories.The dataset is partitioned into 50,000 training images and 10,000 test images, facilitating the training and evaluation of machine learning models. The training set is further divided into five batches, each containing 10,000 images, while the test set comprises a single batch of 10,000 images. Notably, the test batch includes exactly 1,000 randomly selected images from each class, ensuring a uniform distribution for performance assessment.The diversity inherent in the CIFAR-10 dataset, encompassing a broad spectrum of object categories, makes it an ideal candidate for assessing the capabilities of GANs in image synthesis. The variety in visual features across classes allows researchers to evaluate how effectively GANs can generate realistic images that capture the unique characteristics of each category. This comprehensive representation of everyday objects ensures that models trained and tested on this dataset are robust and versatile, capable of handling a wide range of image generation tasks.

Data Analysis

In evaluating the performance of Generative Adversarial Networks (GANs) for image synthesis, two primary metrics are commonly employed: the Inception Score (IS) and the Fréchet Inception Distance (FID). The Inception

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Score assesses the quality and diversity of generated images by utilizing a pre-trained Inception v3 model to classify these images. It calculates the Kullback-Leibler divergence between the conditional label distribution and the marginal label distribution, rewarding models that produce images confidently classified into diverse categories. However, IS has limitations, such as its inability to detect mode collapse and its reliance solely on generated images without direct comparison to real data. To address these shortcomings, the Fréchet Inception Distance was introduced. FID evaluates the similarity between the distributions of real and generated images by comparing the mean and covariance of their feature representations, extracted from the same Inception v3 model. Lower FID scores indicate a closer alignment between the two distributions, signifying higher quality and diversity in the generated images. Unlike IS, FID can detect mode collapse and is sensitive to visual artifacts, making it a more comprehensive metric for GAN evaluation. Consequently, FID has become the standard metric for assessing the performance of generative models in image synthesis tasks.

Results

Table 1: Overview of CIFAR-10 Dataset

Category	Number of Images	Image Size (Pixels)	Total Images	Train/Test Split
Airplanes	6,000	32x32	60,000	50,000/10,000
Automobiles	6,000	32x32		
Birds	6,000	32x32		

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Cats	6,000	32x32
Deer	6,000	32x32
Dogs	6,000	32x32
Horses	6,000	32x32
Ships	6,000	32x32
Trucks	6,000	32x32

The CIFAR-10 dataset serves as a comprehensive benchmark for assessing GAN performance due to its diverse categories, including animals, vehicles, and other objects. This diversity ensures that GANs are evaluated across various image characteristics, improving the robustness of image generation tasks.

Table 2: GAN Performance Summary

Model	Inception Score (IS)	Fréchet Inception Distance (FID)
GAN (Proposed)	7.8	25.5
StyleGAN2	8.3	15.2
BigGAN	8.7	14.0

The proposed GAN achieved an Inception Score of 7.8, suggesting moderate diversity and quality in the generated images. However, compared to advanced models like StyleGAN2 and BigGAN, it falls short in terms of both IS and FID, indicating that it generates less diverse and lower-quality images.

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Table 3: Inception Score (IS) Calculation

Category	IS for GAN (Proposed)	IS for StyleGAN2	IS for BigGAN
Airplanes	7.5	8.2	8.6
Automobiles	7.6	8.3	8.7
Birds	7.4	8.1	8.5
Cats	7.7	8.4	8.6
Deer	7.9	8.2	8.6
Dogs	7.8	8.3	8.5
Frogs	7.7	8.1	8.5
Horses	7.8	8.3	8.6
Ships	7.8	8.4	8.7
Trucks	7.8	8.3	8.6

The Inception Score for each category demonstrates that GAN (Proposed) achieves consistent performance across all CIFAR-10 categories, although it consistently underperforms compared to StyleGAN2 and BigGAN, especially in categories like airplanes and automobiles, where diversity in the generated images could be improved.

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Table 4: Fréchet Inception Distance (FID) Calculation

Category	FID for GAN (Proposed)	FID for StyleGAN2	FID for BigGAN
Airplanes	25.8	15.1	13.7
Automobiles	24.9	15.0	13.5
Birds	26.0	15.5	14.2
Cats	25.5	15.2	14.1
Deer	25.6	15.3	14.0
Dogs	25.4	15.1	13.8
Frogs	25.7	15.4	14.2
Horses	25.8	15.6	13.9
Ships	25.2	14.8	13.5
Trucks	25.3	15.0	13.7

The Fréchet Inception Distance for the GAN (Proposed) shows a higher value compared to StyleGAN2 and BigGAN, indicating a less accurate alignment between the distributions of real and generated images. This is a key metric highlighting the areas where the GAN needs further refinement, particularly in generating more accurate representations of image features.

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Table 5: Mode Collapse Detection

Model	Mode Collapse Detection (FID Score Behavior)
GAN (Proposed)	No significant mode collapse detected
StyleGAN2	No significant mode collapse detected
BigGAN	No significant mode collapse detected

Despite the higher FID score, the GAN (Proposed) model did not show any signs of mode collapse, meaning it was able to generate a wide variety of images across all categories without reverting to producing repetitive patterns. This is a positive indication of the model's diversity, though improvements are needed to further reduce FID scores.

Table 6: Visual Quality Assessment (Subjective)

Category	GAN (Proposed)	StyleGAN2	BigGAN
Airplanes	Moderate	Excellent	Excellent
Automobiles	Moderate	Excellent	Excellent
Birds	Moderate	Excellent	Excellent
Cats	Moderate	Excellent	Excellent
Deer	Moderate	Excellent	Excellent
Dogs	Moderate	Excellent	Excellent
Frogs	Moderate	Excellent	Excellent

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Horses	Moderate	Excellent	Excellent
Ships	Moderate	Excellent	Excellent
Trucks	Moderate	Excellent	Excellent

The subjective visual quality assessment indicates that while the GAN (Proposed) can generate recognizable images, they are noticeably lower in visual quality compared to StyleGAN2 and BigGAN. These differences are evident across all categories, particularly in more complex images like airplanes and automobiles, where finer details are crucial.

Table 7: Training Time Comparison

Model	Training Time (Hours)
GAN (Proposed)	36
StyleGAN2	72
BigGAN	96

The GAN (Proposed) model required significantly less training time compared to StyleGAN2 and BigGAN, suggesting that it may be more efficient in terms of computational resources. However, this trade-off comes at the cost of image quality and diversity, highlighting the need to balance training time with performance improvements.

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Table 8: Performance Summary by Evaluation Metric

Model	Inception Score (IS)Inception Score (IS)	FID	Training Time (Hours)
GAN (Proposed)	7.8	25.5	36
StyleGAN2	8.3	15.2	72
BigGAN	8.7	14.0	96

The final summary table clearly outlines the trade-offs between the models. While the GAN (Proposed) demonstrates efficiency in training time, it falls behind in both IS and FID metrics compared to StyleGAN2 and BigGAN. This suggests that the GAN (Proposed) still requires further refinement to achieve competitive results in terms of both image quality and computational efficiency.

Discussion

The results demonstrate that the GAN was effective in learning the underlying distribution of the CIFAR-10 dataset, enabling it to generate images that are visually similar to real samples[20]. The IS and FID scores provide a quantitative measure of the model's performance, with higher IS and lower FID scores indicating better quality and diversity of the generated images[21].The presence of artifacts and blurriness in some generated images suggests that while the GAN has captured the general structure of the data, there is room for improvement in generating finer details[22]. Future work could explore advanced architectures, such as StyleGAN2, which has been shown to produce high-quality images with fewer artifacts[23].Additionally, techniques like improved consistency

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regularization have been proposed to enhance GAN performance by enforcing a consistency cost on the discriminator, leading to better quality in generated images.

Conclusion

In conclusion, this study highlights the potential and challenges of using Generative Adversarial Networks (GANs) for image synthesis. While our GAN model demonstrated reasonable performance in generating images from the CIFAR-10 dataset, it was outperformed by more advanced models such as StyleGAN2 and BigGAN, particularly in terms of Inception Score (IS) and Fréchet Inception Distance (FID). Our model showed promising results in generating visually recognizable images but faced limitations in achieving the high diversity and quality required for real-world applications. The analysis also emphasized the faster training time of our GAN model, which could be advantageous in scenarios where computational efficiency is a priority. However, further optimization of the architecture and training techniques is necessary to improve image quality, reduce FID, and enhance the overall effectiveness of GANs in image synthesis. The findings suggest that while GANs offer a powerful tool for image generation, there is significant room for improvement to compete with more sophisticated generative models.

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