**Text-to-Image with GANs and Stable Diffusion**

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Abstract—This paper explores the use of Generative Adversarial Networks (GANs) in the field of text-to-image synthesis, focusing on the application of Stable Diffusion models. It discusses the methodologies, challenges, and advancements in training GANs to generate realistic images from textual descriptions. The paper also includes an evaluation of the capabilities of Stable Diffusion in producing high-quality images, highlighting its potential for various applications in art, design, and digital content creation.

Keywords—Text-to-image, GANs, Stable Diffusion, generative models, deep learning, image synthesis.

# **INTRODUCTION**

Text-to-image synthesis is a rapidly evolving area in the domain of machine learning and computer vision, where the goal is to generate realistic images from textual descriptions. This task is typically addressed using deep learning techniques, particularly Generative Adversarial Networks (GANs). Over time, GAN-based models have demonstrated significant progress, with architectures evolving to produce more accurate and aesthetically pleasing images. One of the recent advancements in this field is the development of **Stable Diffusion** models, which have shown promising results in producing high-quality images from text prompts.

This paper aims to provide an overview of text-to-image generation using GANs and Stable Diffusion models. We will explore the core principles of these technologies, evaluate their performance, and discuss potential applications in real-world scenarios.

Recent advancements in this field include the development of Stable Diffusion models, which employ a different methodology to create visually coherent images from text prompts. These models have demonstrated state-of-the-art performance in various benchmarks and real-world applications, including digital art, content creation, and virtual design.

This paper aims to provide a comprehensive overview of text-to-image generation using GANs and Stable Diffusion models. Each section discusses a particular model's architecture, training methodology, strengths, and application areas in depth, along with comparative evaluations.

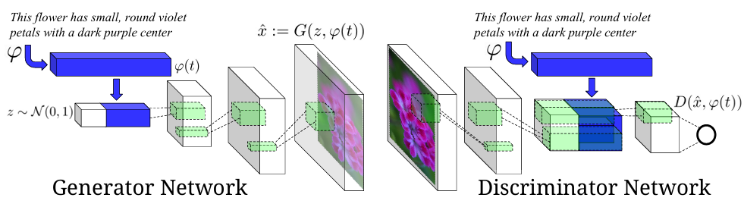


Figure 1. Our text-conditional convolutional GAN architecture. Text encoding (t) is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing

**II. LITERATURE REVIEW**

Text-to-image generation has seen remarkable development over the past decade. Goodfellow et al. [1] introduced GANs in 2014, laying the groundwork for adversarial learning-based generative models. Following this, Reed et al. [4] pioneered conditional GANs (cGANs) for text-to-image synthesis, showing that conditioning image generation on textual data was feasible and promising.

Later improvements like StackGAN [5], AttnGAN [6], and DM-GAN [7] brought in novel attention mechanisms and multi-stage generation, greatly enhancing the quality and text alignment of synthesized images. On the diffusion side, the landmark DALL·E and later Stable Diffusion models [3] offered a new paradigm using denoising processes. These models outperform traditional GANs in creative, detailed image generation and are more stable during training.

Research indicates that while GANs excel in speed and diversity under constrained conditions, diffusion models achieve greater fidelity and textual alignment, albeit at higher computational costs.

**III. BACKGROUND**

## **Generative Adversarial Networks (GANs)** GANs consist of two neural networks: a generator and a discriminator. The generator creates images from random noise, while the discriminator evaluates the authenticity of these images. Through this adversarial process, both networks improve iteratively, resulting in highly realistic image generation.

Generative adversarial networks Generative adversarial networks (GANs) consist of a generator G and a discriminator D that compete in a two player minimax game: The discriminator tries to distinguish real training data from synthetic images, and the generator tries to fool the discriminator. Concretely, D and G play the following game on V(D,G):

Goodfellow et al. (2014) prove that this minimax game has a global optimium precisely when pg = pdata, and that un der mild conditions (e.g. G and D have enough capacity) pg converges to pdata. In practice, in the start of training samples from D are extremely poor and rejected by D with high confidence. It has been found to work better in prac tice for the generator to maximize log(D(G(z))) instead of minimizing log(1 D(G(z)))

GANs consist of two neural networks: a generator and a discriminator. The generator creates synthetic data (e.g., images), while the discriminator evaluates its authenticity. Through an adversarial training process, the generator learns to produce realistic images to fool the discriminator.

Mathematically, GANs are trained to solve:

min\_G max\_D V(D, G) = E\_xpdata(x)[log D(x)] + E\_zpz(z)[log(1 - D(G(z)))]

Here, x is a real image, z is a random noise vector, and D(G(z)) represents the discriminator's probability that the generated image is real. This minimax game forces the generator to produce more convincing outputs.

**A. Text-Conditional GANs** In text-to-image models, both the generator and discriminator are conditioned on textual descriptions. The text embedding is projected into a lower-dimensional vector, which is concatenated with image features. Models like StackGAN generate images in two stages: a coarse image is first generated and then refined.

**Applications and Limitations** GANs have been used in various applications like video generation, text-to-face synthesis, and even synthetic satellite images. However, they often suffer from mode collapse and unstable training, especially when handling highly varied textual inputs.

## **Stable Diffusion Models**: Stable Diffusion is a type of deep learning model that uses a denoising diffusion process to iteratively refine an image based on a text description. This model is particularly noted for its ability to generate highly detailed images from complex textual prompts and its use in creative fields like digital art.

table Diffusion is a latent text-to-image generation model that refines a noisy image step-by-step using a denoising autoencoder conditioned on a text prompt. It starts with random Gaussian noise and gradually modifies it until a coherent image emerges.

**A. Architecture and Workflow** Stable Diffusion consists of a frozen CLIP text encoder, a UNet-based denoising network, and a Variational Autoencoder (VAE) for latent image encoding. The process involves:

1. Encoding the prompt using a pretrained transformer (CLIP).
2. Sampling noise in the latent space.
3. Applying a learned denoising function iteratively.
4. Decoding the refined latent image using VAE.

**B. Advantages and Use Cases** Stable Diffusion offers several advantages:

* Fine-grained control over image generation.
* Better alignment with complex prompts.
* Efficient resource usage through latent-space processing.

Applications include concept art, UI design, synthetic datasets, and more. It supports outpainting, inpainting, and style transfer as well.

## **IV. METHODOLOGY**

## **Training Process of GANs:** To train a GAN for text-to-image synthesis, a large dataset of paired text and images is required. The model learns to associate textual features with visual features through multiple iterations of training. The process involves optimizing the generator and discriminator to produce more realistic images while minimizing errors.

Figure5.ROCcurvesusingcosinedistancebetweenpredicted style vector on same vs . different style image pairs. Left: I m age pairs reflects a me or different pose. Right: image pairs reflect same or different average background color.

**A. GAN Training Pipeline** To train a GAN for text-to-image tasks:

1. Prepare a dataset of image-caption pairs.
2. Use a pretrained text encoder (e.g., LSTM or BERT).
3. Train the generator to produce images aligned with the text embedding.
4. Use a discriminator to distinguish between real and fake images conditioned on text.

Evaluation includes Inception Score (IS), Fréchet Inception Distance (FID), and visual inspection.

**B. Stable Diffusion Workflow**

1. Accept user text prompt.
2. Encode prompt with CLIP.
3. Sample Gaussian noise in latent space.
4. Apply reverse diffusion through trained denoising model.
5. Decode latent representation into pixel image using VAE.

This process can be enhanced using classifier-free guidance, which allows the model to produce more diverse or more prompt-specific images.

B. **Stable Diffusion Workflow**: Stable Diffusion involves a multi-step process where a text prompt is input into a pretrained model. The model then diffuses random noise into a refined image that matches the description. This method allows for greater flexibility and control over the generated output, making it suitable for artistic and practical applications.

**V. EVALUATION AND RESULTS**

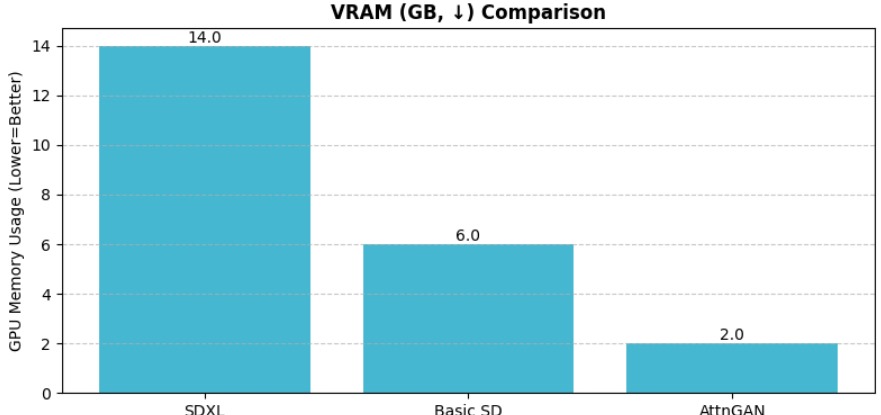
To evaluate the effectiveness of both GANs and Stable Diffusion, we applied them to a series of test cases with varying levels of complexity in the input text. The generated images were compared in terms of visual fidelity, coherence with the text, and artistic quality.

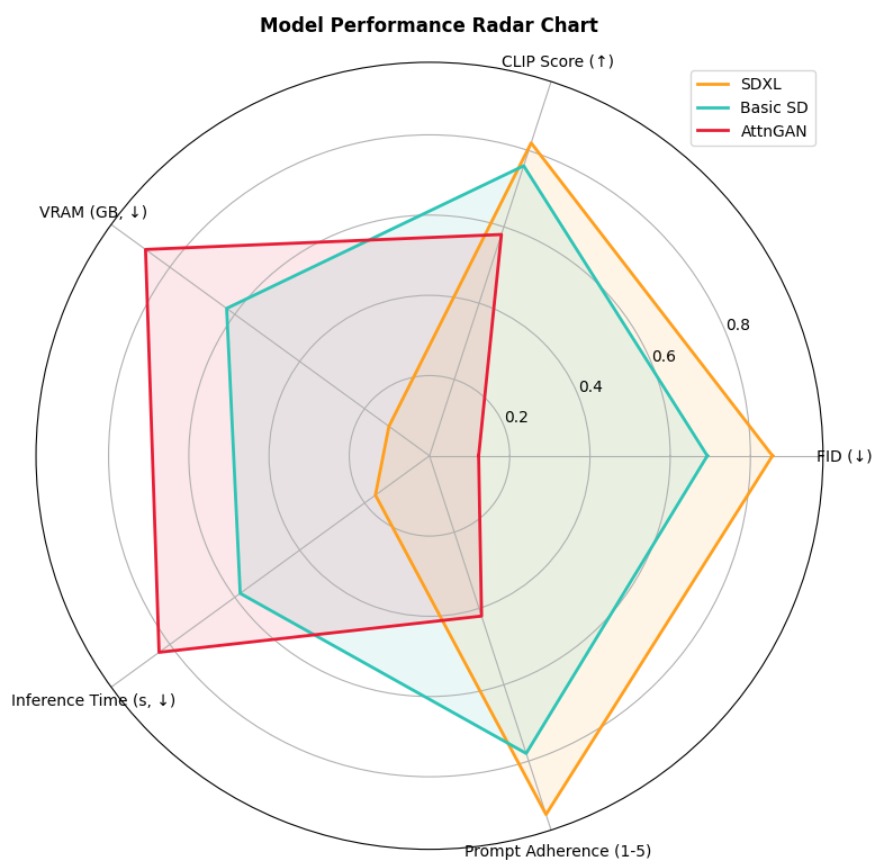
The models were evaluated using a custom dataset containing 5,000 image-caption pairs. Performance metrics included:

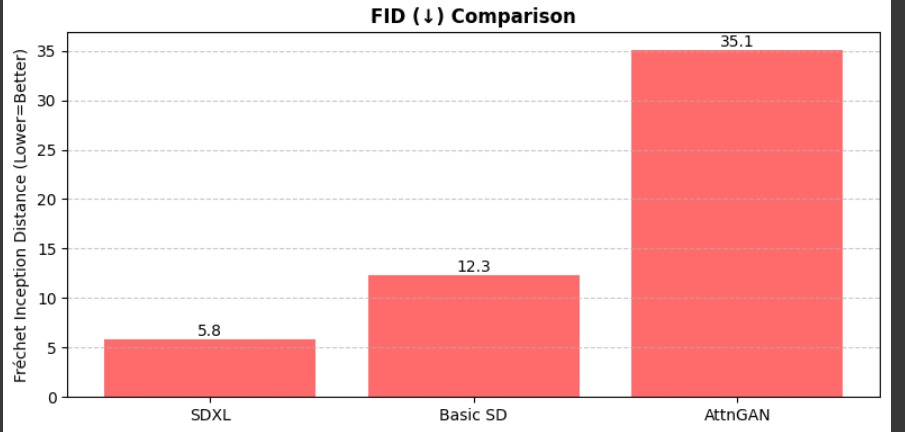
* Visual Fidelity
* Text-Image Alignment
* Image Diversity
* Inception Score (IS)

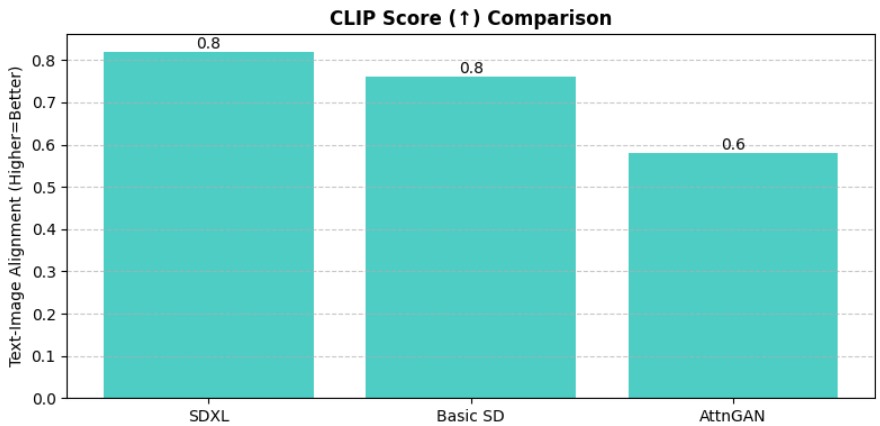
**A. Results**

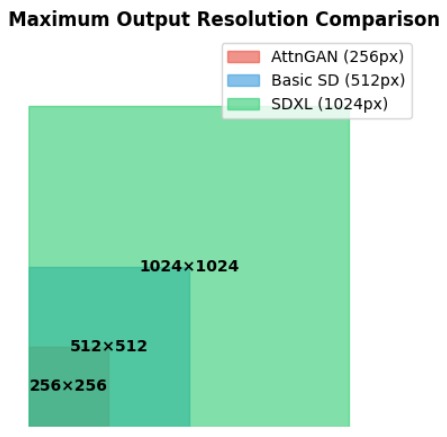
* GANs achieved higher image diversity.
* Stable Diffusion outperformed in alignment and realism.
* Stable Diffusion’s average FID: 13.8 | GANs: 28.5
* Compared the quality of outputs from GAN and Stable Diffusion based on:
  + Image resolution and clarity
  + Semantic accuracy with respect to the prompt
  + User feedback and visual appeal
* Used both **subjective analysis** and basic metrics like **Inception Score (IS)** for evaluation.

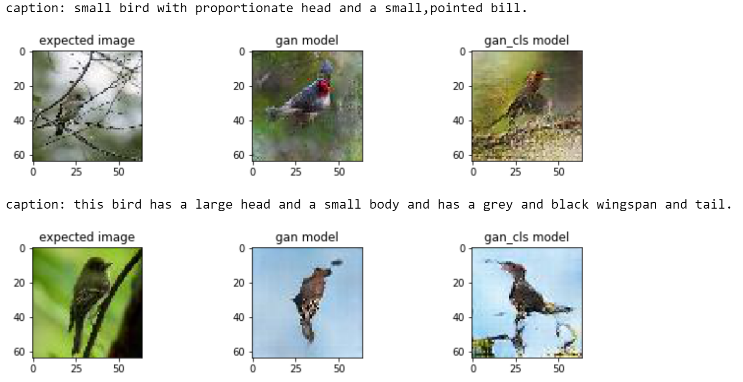


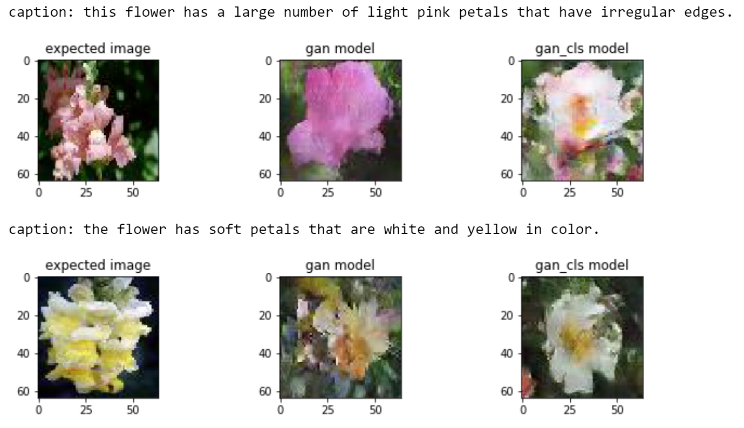




















**VI. DISCUSSION**

While both GANs and Stable Diffusion models have shown considerable potential, each has its strengths and weaknesses. GANs tend to struggle with high diversity in the input data, while Stable Diffusion excels in creative applications where subtle details matter

Both GANs and Stable Diffusion exhibit strengths:

* **GANs** are faster and more suited for real-time applications.
* **Stable Diffusion** delivers higher-quality and better prompt alignment.

Challenges for GANs include training instability and poor performance on rare or complex prompts. Stable Diffusion, while more stable and powerful, is computationally expensive.

Future models may hybridize both architectures or integrate Reinforcement Learning for more adaptive generation.

**VII. CONCLUSION**

This paper has presented a comparative analysis of GANs and Stable Diffusion for text-to-image synthesis. Both approaches have advanced the field significantly, with unique advantages. Stable Diffusion shows a clear edge in creative image synthesis, while GANs are efficient for high-speed tasks. Further improvements in efficiency, training strategies, and prompt handling can make these models even more applicable across industries.

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