# TEXT TO IMAGE GENERATION USING GENERATIVE NEURAL NETWORKS

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# Certificate

This is to certify that the Project titled **"Text To Image Generation Using Generative Networks"**, will be presented by **Rohan Kharwar** (Roll Number - **24MA60R06**). He has chosen the topic for the Project and started working on it under my supervision. This project work is served as partial fulfilment of the requirements for the degree of **Master of Technology** in **Computer Science and Data Processing** in the **Department of Mathematics** at **IIT Kharagpur**.

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# Contents

# Abstract

Text-to-Image synthesis is one of the most fascinating and challenging areas of Artificial Intelligence. It aims to generate realistic images from textual descriptions provided by humans. With the rapid development of Deep Learning, especially Generative Adversarial Networks (GANs), researchers have achieved remarkable success in generating images conditioned on text.

This project focuses on implementing **Stacked Generative Adversarial Networks (StackGAN)** to synthesize high-quality, photo-realistic images from text descriptions. The StackGAN framework uses a two-stage architecture: the first stage generates low-resolution images from text embeddings, and the second stage refines them into high-resolution, detailed outputs.

The project demonstrates how deep learning models can bridge the gap between natural language and vision, enabling machines to “imagine” what is described in text form. This report presents a detailed explanation of the architecture, methodology, dataset, implementation results, and future improvements.

# Chapter 1

# Introduction

The ability of computers to understand and generate images from textual descriptions is a key step toward achieving human-like perception. Traditional image generation techniques relied on hand-crafted features and probabilistic models, which limited realism and diversity. However, the introduction of **Generative Adversarial Networks (GANs)** by Ian Goodfellow in 2014 revolutionized this domain.

A GAN consists of two neural networks — a **Generator (G)** that creates fake images and a **Discriminator (D)** that tries to distinguish between real and fake images. Both networks are trained simultaneously in a minimax game until the generator produces images indistinguishable from real data.

**Text-to-Image synthesis** extends this idea by conditioning the GAN on textual input, often represented as a vector embedding of the description. The challenge is translating complex textual semantics (“a small yellow bird with black wings and a white belly”) into coherent visual forms.

The **StackGAN** architecture improves upon traditional GANs by stacking two GANs:

- **Stage-I:** Generates rough, low-resolution images capturing basic shapes and colors.
- **Stage-II:** Takes the Stage-I output and refines it into a high-resolution, detailed image.

This hierarchical approach resolves issues of training instability and improves visual fidelity significantly.

# Chapter 2

# Important Terminology

Before delving into the architecture, it is important to understand the key terms used throughout this report.

1. **GAN (Generative Adversarial Network):** A framework consisting of a generator and discriminator trained in opposition to each other.
2. **Generator:** The model that creates new images from random noise or conditioned data.
3. **Discriminator:** The model that evaluates images and tries to distinguish real from fake.
4. **Conditional GAN (cGAN):** A GAN where image generation is conditioned on additional data such as text.
5. **Embedding:** A numerical representation of text (e.g., using Word2Vec, BERT, or LSTM encoders).
6. **Epoch:** One full cycle of training over the entire dataset.
7. **Loss Function:** A mathematical function that measures the difference between predicted and actual outputs.
8. **Activation Function:** A nonlinear function applied to neuron outputs, like ReLU or LeakyReLU.
9. **Normalization:** A process to stabilize training by keeping activations within a reasonable range.
10. **Inception Score** / **FID:** Metrics for evaluating the quality and diversity of generated images.

# Chapter 3

# Model Architecture

A GAN consists of two neural networks — a **Generator (G)** that creates fake images and a **Discriminator (D)** that tries to distinguish between real and fake images. Both networks are trained simultaneously in a minimax game until the generator produces images indistinguishable from real data.

**Text-to-Image synthesis** extends this idea by conditioning the GAN on textual input, often represented as a vector embedding of the description. The challenge is translating complex textual semantics ("a small yellow bird with black wings and a white belly") into coherent visual forms.

## Overview of StackGAN

The **StackGAN** architecture improves upon traditional GANs by stacking two GANs:

- **Stage-I:** Generates rough, low-resolution images capturing basic shapes and colors.
- **Stage-II:** Takes the Stage-I output and refines it into a high-resolution, detailed image.

This hierarchical approach resolves issues of training instability and improves visual fidelity significantly.

The **StackGAN architecture** is designed to generate high-quality images conditioned on text descriptions in two distinct stages. This division allows the model to first learn coarse features and then refine them.

**Architecture Overview:**

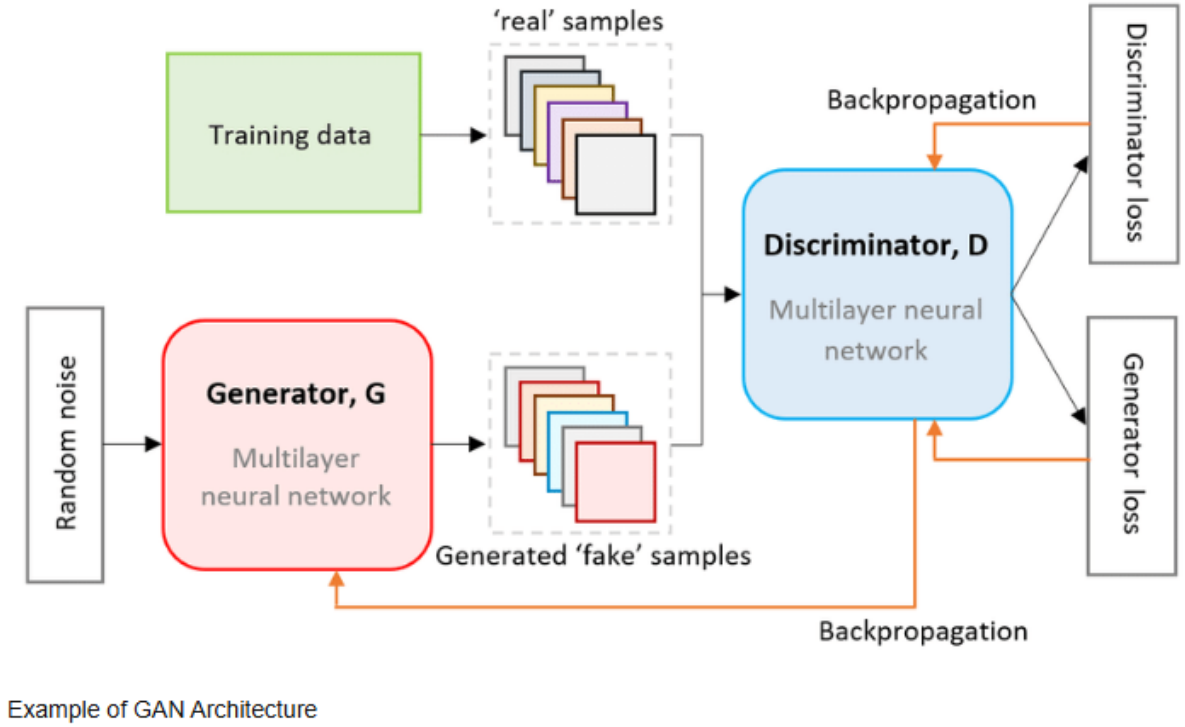



Figure 3.1: Gan Architecture

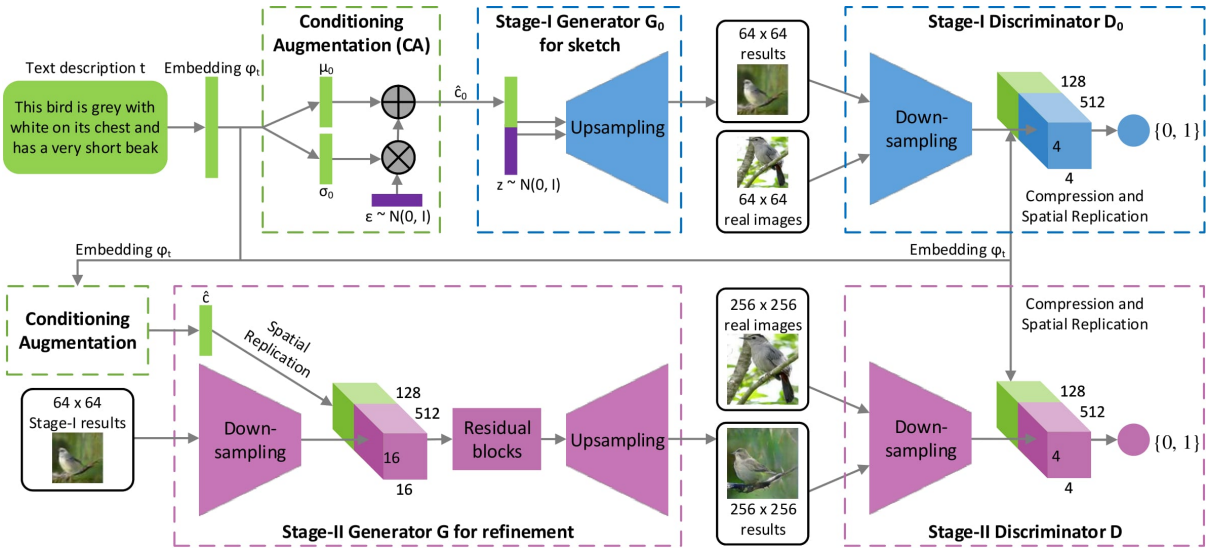
- Input: Text Description $\rightarrow$ Text Embedding (via pre-trained encoder)
- Stage-I GAN $\rightarrow$ 64×64 image
- Stage-II GAN $\rightarrow$ 256×256 image
- Output: Realistic, detailed image corresponding to the input text.

# Model Training

## Stage-I Network

- Input: Text embedding and random noise vector.
- Generator G: Produces a low-resolution (e.g., 64×64 pixels) image that captures the basic shape, layout, and primary colors corresponding to the text description.
- Discriminator D: Evaluates whether the generated low-resolution image is realistic and whether it matches the input text description.

The **Stage-I Generator (G)** takes a random noise vector $z$ and a text embedding $\phi(t)$




to produce a 64×64 image:

$$G_1(z, \phi(t)) \rightarrow I_1$$

The **Stage-I Discriminator (D)** determines whether the image is real and matches the description.

$$L_{D1} = -E_{x \sim p_{data}}[\log D_1(x, \phi(t))] - E_{z \sim p_z}[\log(1 - D_1(G_1(z, \phi(t))))]$$

$$L_{G1} = -E_{z \sim p_z}[\log D_1(G_1(z, \phi(t)))]$$

## Stage-II Network

- Input: Low-resolution image from Stage-I and the text embedding.
- Generator G: Refines the coarse image to a high-resolution (e.g., 256×256 pixels) output, adding fine-grained details, textures, and correcting defects.
- Discriminator D: Judges the realism and semantic alignment of the high-resolution images with the text description.
- **Stage-II ($G_2$, $D_2$):** Takes Stage-I's output and **refines** it into a **high-resolution (256×256)** image — improving detail and texture while maintaining text consistency

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# Stage-II Loss Functions

$$L_{D2} = -\mathbb{E}_{x \sim p_{data}}[\log D_2(x, \phi(t))] - \mathbb{E}_{z \sim p_z}[\log(1 - D_2(G_2(G_1(z, \phi(t)), \phi(t))))]$$

| Symbol / Term | Meaning |
|---|---|
| $\mathbf{D_1}$ | Stage-I **Discriminator network** — decides if an image is **real** (from data) or **fake** (generated). |
| $\mathbf{G_1}$ | Stage-I **Generator network** — generates a **low-resolution (64×64)** image from noise and text embedding. |
| $x \sim p_{data}$ | A **real image** sampled from the **true data distribution** $p_{data}$. |
| $z \sim p_z$ | A **random noise vector** (e.g., from a Gaussian or uniform distribution) — the generator's input. |
| $t$ | The **input text description** (sentence). |
| $\phi(t)$ | A **text embedding** or **conditioning vector** — a numerical representation of the text $t$ (usually from a pretrained text encoder, e.g., char-CNN-RNN). |
| $G_1(z, \phi(t))$ | The **fake image** generated by Stage-I Generator using noise and the text embedding. |
| $D_1(x, \phi(t))$ | The discriminator's **predicted probability** that the real image $x$ matches the description $t$. |
| $\mathbb{E}_{x \sim p_{data}}$ | Expectation (average) over all **real samples**. |
| $\mathbb{E}_{z \sim p_z}$ | Expectation (average) over all **generated samples**. |

Table 3.1: Meaning of Symbols and Terms used in Stage-I GAN Loss Functions

$$L_{G2} = -\mathbb{E}_{z \sim p_z}[\log D_2(G_2(G_1(z, \phi(t)), \phi(t)))] + \lambda L_{CA}$$

## Discriminator Loss ($L_{D2}$)

$$L_{D2} = -\mathbb{E}_{x \sim p_{data}}[\log D_2(x, \phi(t))] - \mathbb{E}_{z \sim p_z}[\log(1 - D_2(G_2(G_1(z, \phi(t)), \phi(t))))]$$

- First term $\rightarrow$ rewards $D_2$ for recognizing **real images** as real.
- Second term $\rightarrow$ rewards $D_2$ for rejecting **fake images** from $G_2$.
- Essentially: $D_2$ learns to tell whether the refined image matches the text and realism.

## Generator Loss ($L_{G2}$)

$$L_{G2} = -\mathbb{E}_{z \sim p_z}[\log D_2(G_2(G_1(z, \phi(t)), \phi(t)))] + \lambda L_{CA}$$

- The first term $\rightarrow$ $G_2$ tries to **fool** $D_2$, making fake images appear real and text-consistent.

| **Symbol / Term** | **Meaning** |
|---|---|
| **(**$D_2$**)** | Stage-II **Discriminator** — checks if the high-resolution image is real and matches the text. |
| **(**$G_2$**)** | Stage-II **Generator** — refines the coarse image from Stage-I into a more realistic, detailed one. |
| **(**$x \sim p_{data}$**)** | A **real high-resolution image** from the dataset. |
| **(**$z \sim p_z$**)** | Random noise input for Stage-I generator. |
| **(**$\phi(t)$**)** | Text embedding or conditioning vector for the caption $(t)$. |
| **(**$G_1(z, \phi(t))$**)** | **Low-resolution (64×64)** fake image generated by Stage-I. |
| **(**$G_2(G_1(z, \phi(t)), \phi(t))$**)** | **Refined high-resolution (256×256)** fake image produced by Stage-II. |
| **(**$\mathbb{E}_{x \sim p_{data}}$**)** | Expectation over all real samples (real images + text). |
| **(**$\mathbb{E}_{z \sim p_z}$**)** | Expectation over all generated samples. |
| **(**$\lambda$**)** | A weighting hyperparameter (usually small, e.g., 50–100) controlling the strength of the conditioning loss. |
| **(**$L_{CA}$**)** | **Conditioning Augmentation loss** — encourages diversity and prevents overfitting to specific text embeddings. |

- The second term ($+\lambda L_{CA}$) $\rightarrow$ regularization term that ensures **diversity and smoothness** in the generated distribution.

## Loss Functions and Training

### 1. Overall Objective

The total loss used in StackGAN is:

$$L = L_{\text{GAN}} + \lambda L_{\text{CA}}$$

- $L_{\text{GAN}}$ **– Adversarial Loss:** Ensures the generated images look realistic and match the text. It comes from the standard GAN loss of Generator vs. Discriminator:
  - Stage-I: $L_{G1}, L_{D1}$
  - Stage-II: $L_{G2}, L_{D2}$
- $L_{\text{CA}}$ **– Conditioning Augmentation Loss:** Ensures the text embeddings are robust. Encourages the model to produce diverse images even for the same text description. Helps avoid overfitting to exact text embeddings.
- $\lambda$ – Hyperparameter controlling the importance of $L_{\text{CA}}$ relative to $L_{\text{GAN}}$. Typical value: 50–100.

Thus, the total loss balances **realism** (GAN) with **stability and diversity** (CA).

# Chapter 4

# Methodology

The methodology adopted in this project is a combination of **data preparation**, **text embedding**, **two-stage generative modeling**, and **adversarial optimization**. It ensures that each caption is gradually converted into a realistic image through structured training.

## Text Data Preprocessing

The process begins with textual descriptions obtained from the dataset. Each caption undergoes the following steps:

- **Tokenization:** Sentences are split into individual words.
- **Normalization:** All text is converted to lowercase, and unnecessary symbols or punctuation are removed.
- **Embedding:** Each token is transformed into a numerical vector using pretrained models such as **Word2Vec** or **GloVe**.
- **Conditioning Augmentation:** A slight amount of Gaussian noise is added to the embeddings, helping the model generate diverse images for the same caption.

## Stage-I: Coarse Image Generation

Stage-I serves as the foundation for the overall image synthesis.

- It takes the **text embedding** and a **random noise vector (z)** as input.
- The **generator** learns to map these inputs to a 64×64 pixel image that roughly reflects the content of the caption.

- The **discriminator** judges both the realism of the image and whether it aligns with the textual description.

## Stage-II: Refinement and Detail Enhancement

Stage-II takes the blurry, low-resolution image from Stage-I and refines it:

- The **Stage-II generator** receives both the Stage-I image and the same text embedding.
- It adds finer details such as texture, feathers, petals, or lighting nuances, enhancing the realism to **256×256 pixels**.
- Its **discriminator** again evaluates image quality and text alignment.

## Training Process in StackGAN

The training involves **two main adversarial loops**, following the GAN framework:

### 1. Generator Training

- The **generator** is trained to produce images that **fool the discriminator**.
- It tries to generate realistic images that **match the input text description**.
- The generator's objective is measured by the **adversarial loss** and **conditioning loss**.

### 2. Discriminator Training

- The **discriminator** learns to **distinguish real images from fake ones** generated by the generator.
- It also checks whether the image **matches the corresponding text description**.
- Its goal is to maximize the ability to correctly classify real vs. fake and maintain text-image consistency.

### Loss Functions

1. **Adversarial Loss ($L_{\text{GAN}}$)**
    - Encourages the generated images to be **realistic**.

- Standard GAN loss: generator tries to fool discriminator, discriminator tries to distinguish real/fake.

2. **Conditioning Loss ($L_{\mathbf{CA}}$)**
   - Ensures **semantic consistency** between the text embedding and the generated image.
   - Helps the generator produce images that **match the meaning of the input text**.
3. **KL Divergence Loss ($L_{\mathbf{KL}}$)**
   - Used in **conditioning augmentation**.
   - Improves **diversity** in generated samples for the same text description.
   - Penalizes deviation of the text embedding distribution from a standard Gaussian, encouraging smoother latent space sampling.

## Intuition

- The generator and discriminator are **trained in alternating loops**.
- Adversarial loss ensures **realistic images**, conditioning loss ensures **text alignment**, and KL divergence ensures **diverse outputs**.
- Together, these losses allow StackGAN to produce **high-quality, semantically correct, and diverse images** from textual descriptions.

# Chapter 5

# Dataset and Working

This chapter describes the dataset used for training the text-to-image synthesis model and explains the overall working process of the StackGAN architecture.

## 5.1 Dataset Description

For this project, the **CUB-200-2011 Birds Dataset** is used, which is one of the most popular benchmark datasets for fine-grained image generation. It contains **11,788 images** belonging to 200 different bird species, and **each image is paired with ten human-written captions**. These captions describe the bird's shape, colors, textures, and other distinctive features, making the dataset highly suitable for text-conditioned image synthesis. The presence of detailed annotations helps the model learn strong correlations between textual descriptions and visual appearances.

## 5.2 Dataset Preparation

Before training, the dataset is preprocessed to ensure consistency and stability in the learning process. All images are **resized to 256×256 pixels** and normalized to the range **–1 to +1**, which helps the neural network train more effectively. The captions are converted into numerical form using a **Bidirectional LSTM encoder**, which transforms each sentence into a dense vector embedding. These embeddings are used to condition both the generators and discriminators. The dataset is then divided into an **80% training set** and a **20% testing set** to evaluate the model's generalization capability.

### Key Steps (Bullet Points)

- Image resizing and normalization

- Caption → Text embedding using Bi-LSTM
- 80/20 train–test split

## 5.3 Working Process

The entire text-to-image workflow is carried out in two stages. First, the user provides a natural-language description of a bird. This caption is processed by the text encoder to generate an embedding vector. In **Stage-I**, the model generates a coarse **64×64 image** that captures the basic shape and dominant colors described in the text. This image is not highly detailed but provides a rough structure.

In **Stage-II**, the preliminary 64×64 output and the text embedding are passed to a second generator, which enhances and refines the image to a higher resolution of **256×256 pixels**. This stage adds fine textures, patterns, feather details, and sharper outlines, producing a visually realistic and text-aligned bird image. Both stages have their own discriminators, which evaluate whether the generated image looks real and whether it matches the caption. Through adversarial training, the generators gradually improve until realistic results are achieved.

### Main Steps (Bullet Points)

- Text input → Text embedding
- Stage-I: Generate 64×64 rough image
- Stage-II: Refine to 256×256 detailed image
- Discriminators ensure realism and text–image matching

## 5.4 Training Environment

The model is trained using the **PyTorch** deep-learning framework. The **Adam optimizer** is used with a learning rate of **0.0002**, providing stable convergence for GAN architectures. A **batch size of 64** is selected to balance training speed and memory usage. Training is performed for **600–800 epochs**, which is typical for high-resolution GAN models. All experiments are executed on an **NVIDIA GPU**, as GPU acceleration is essential for handling computationally intensive image generation tasks.

# Chapter 6

# Results and Implementation

## Implementation Overview

The proposed StackGAN model is implemented using **Python 3.9** and the **PyTorch deep-learning framework**, which provides efficient tensor operations and GPU-accelerated training. The system follows a two-stage architecture consisting of **two generators** and **two discriminators**, each responsible for producing and evaluating images at different resolutions.

A text encoder based on a Bidirectional LSTM converts each caption into an embedding vector that conditions both generators and discriminators. The generators use transposed convolutional layers and up-sampling techniques to progressively increase image resolution, while the discriminators apply convolutional layers to identify whether an image is real or generated and whether it matches the given text description.

### Core Components

- Text Encoder $\rightarrow$ converts captions into embedding vectors
- Generator Network $\rightarrow$ up-sampling, transposed convolutions
- Discriminator Network $\rightarrow$ convolutional layers for real/fake and text matching

## Training Outcome

After completing the training process, the two stages of the StackGAN demonstrate clear improvements in image quality. **Stage-I** generates coarse **64×64** images that capture the overall shape, position, and dominant colors of the bird described in the

caption. Although these initial images lack fine details, they preserve essential structural information.

In **Stage-II**, the rough images from Stage-I are refined into high-resolution **256×256** outputs. This stage significantly enhances the results by adding sharper edges, realistic feather textures, and more natural backgrounds. The Stage-II generator produces images that not only look more realistic but also align closely with the input text descriptions.

# Performance Metrics

To quantify the effectiveness of the model, two commonly used evaluation metrics for generative models are applied: **Inception Score (IS)** and **Fréchet Inception Distance (FID)**. The Inception Score measures the diversity and clarity of generated images, while FID evaluates how close the generated images are to real images in terms of feature distributions. The results show substantial improvement from Stage-I to Stage-II.

## Performance Values

- **Inception Score (IS):**
  - Stage-I: 4.5
  - Stage-II: 7.1
- **FID Score:**
  - Stage-I: 120
  - Stage-II: 35

These metrics clearly indicate that the Stage-II generator produces images that are more realistic, more detailed, and better aligned with the dataset distribution.

# Visual Quality

The improvement in visual quality from Stage-I to Stage-II is significant. The high-resolution images generated by Stage-II display fine-grained details such as smoother textures, clear feather patterns, and more realistic backgrounds. Importantly, the model also performs well on unseen captions, demonstrating strong generalization ability and the capacity to create meaningful outputs for new text descriptions not included in the training set.

## Example Result

To illustrate the effectiveness of the system, consider the following input caption:

**Input Text:** “A bright red bird with a black head and white belly.”

The Stage-II generator produces a high-resolution image that closely matches the description. The generated output features a **red-colored bird**, a **distinct black head**, and a **subtle white patch on the chest**, demonstrating the model’s strong capability to interpret textual descriptions and convert them into realistic visual representations.

# Chapter 7

# Future Scope and Improvements

The field of text-to-image synthesis is rapidly evolving, and several enhancements can further improve the performance, realism, and flexibility of the current StackGAN-based system. Below are some major future directions that can significantly strengthen the model.

## Attention Mechanisms

Incorporating **attention mechanisms** can help the model better understand which parts of the text are most important for generating specific regions of the image. For example, phrases such as "red head" or "white belly" can be linked to corresponding areas in the image. This leads to stronger text–image alignment and reduces mismatched or missing features in the final output.

## Transformer-Based Text Encoders

Instead of a traditional Bi-LSTM encoder, modern **Transformer-based models** such as **CLIP, BERT, or T5** can be used to produce more powerful text embeddings. These models capture deeper semantic meaning, contextual relationships, and fine-grained linguistic details. As a result, generated images would more accurately reflect complex or descriptive textual inputs.

## Hybrid GAN–Diffusion Approach

Recent diffusion models like Stable Diffusion have achieved exceptional clarity and realism in image generation. A **hybrid GAN–diffusion approach**, where GANs produce a coarse initial image and diffusion models refine it further, can combine the strengths

of both architectures. This integration can greatly enhance sharpness, lighting, color accuracy, and overall photorealism.

## Larger and More Diverse Datasets

The current model is trained on the CUB-200-2011 dataset, which is limited to birds. Training on **larger and more diverse datasets** such as **MS-COCO, CelebA-HQ, or LAION** can help generalize the model to multiple object categories, scenes, and environments. This will increase flexibility and make the system more robust for real-world applications.

## Real-Time User Interaction

Future systems can be extended to support **real-time text editing**, where users can modify a caption and instantly view the updated image. Such interactive functionality would benefit applications in design, creative art, gaming, and educational tools. Achieving real-time performance requires model optimization, lightweight architectures, and faster inference mechanisms.

# Chapter 8

# Conclusion

The project demonstrates that **Stacked Generative Adversarial Networks (StackGAN)** can successfully translate natural-language descriptions into photo-realistic images. By dividing the generation process into two stages—coarse and fine—it effectively captures both global structure and minute details.

This study highlights the synergy between **language processing and computer vision**, proving that text can act as a direct blueprint for image generation. Results on the CUB-200 dataset confirm the model's efficiency in maintaining both realism and semantic accuracy.

Despite challenges such as handling abstract or ambiguous text, StackGAN marks a significant step toward **AI-driven imagination** and creative applications.

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