

# Generative Adversarial Networks (GANs) in Image Generation

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## 1. Justification

### Innovative Potential:

GANs offer a cost-effective alternative to networks like DALL-E, making them appealing to industries seeking efficient AI-driven content creation.

### Market Demand:

Industries like gaming, film, and marketing increasingly rely on AI-generated content to save time and reduce costs.

### Applications:

- **Art:** Creation of unique digital artwork.
- **Content Creation:** Quick generation of gaming and media assets.
- **Data Augmentation:** Enhancing datasets for training other AI models.

Despite GANs' competitive limitations compared to modern genAI solutions, this project aims to explore and optimize their performance using current techniques and resources.

## 2. Project Scope

### Primary Focus:

Build a GAN-based system for generating high-quality images, exploring architecture optimizations to improve performance.

### Secondary Focus:

- Investigate modern alternatives like TransGAN.
- Evaluate results using limited computational resources.

### Research Objectives:

Study the impact of different GAN architectures on image quality and diversity.

### Practical Applications:

- AI-driven art creation.
- Synthetic data generation for training other AI models.

## 3. Goal / Aims

### Main Objective:

Develop a high-performance GAN capable of generating photorealistic images.

### Sub-Goals:

- Enhance training stability and minimize artifacts in generated images.

- Compare the performance of various GAN architectures.
- Implement a user interface to generate images.

#### 4. Features to be Implemented

##### Primary Features (Must-Have):

- **GAN Architecture Implementation:** Use standard or DCGAN architectures.
- **Dataset Preparation:** Preprocess and train on a large dataset.
- **Training and Tuning:** Set up training pipelines with hyperparameter tuning.
- **Evaluation Metrics:** Measure image quality using Inception Score and FID.

##### Secondary Features (Nice-to-Have):

- Explore **TransGAN** architecture.
- Develop an easy-to-use UI for generating images.

#### 5. Techniques & Technologies

- **Core Technology:** GAN, WGAN, TransGAN, each network trained for roughly 12 hours
- **Programming Language:** Python.
- **Frameworks:** PyTorch
- **Infrastructure:** Google Collab, and Local Learning
- **Datasets:** 39,000 source images depicting cats

#### 6. Short State of the Art

##### Competitive Solutions:

- **DCGANs:** Higher-quality results using convolutional layers.
- **Conditional GANs (cGANs):** Enables generation based on labels or conditions (e.g., specific objects).
- **StyleGAN:** Advanced model capable of detailed photorealistic generation.

##### Emerging Techniques:

- **Visual Transformers:** Adapted for 2D images, transforming AI generative tasks.
- **Diffusion Networks:** Primarily generative, contrasting traditional transformers.

##### Challenges:

- Mode collapse, training instability, dataset size, and high computational costs

#### 7. Implementation Description

##### Development Steps:

1. Conducted a literature review on GANs and their existing implementations.
2. Prepared the dataset through preprocessing.
3. Implemented and trained the models using PyTorch.

4. Fine-tuned hyperparameters and evaluated model performance.
5. Prepared a UI for image generation.

#### **Deployment Requirements:**

- **Hardware:** High-performance GPU (e.g., NVIDIA).
- **Software:** PyTorch, Python, cloud computing services .
- **Installation Steps:**
  - Set up the development environment with required libraries.
  - Download code from repository  
([https://github.com/JanRucinski/MMCV\\_MON0730\\_GAN\\_IMAGE\\_GEN](https://github.com/JanRucinski/MMCV_MON0730_GAN_IMAGE_GEN))
  - Train the model on the dataset.
  - Run the UI (UI.py)

#### **8. Conclusions**

- GAN training is heavily reliant on resources.
- Different architectures present various problems.