



Academy of  
Engineering

School of Computer Engineering

# Face Generation using DCGAN and CGAN

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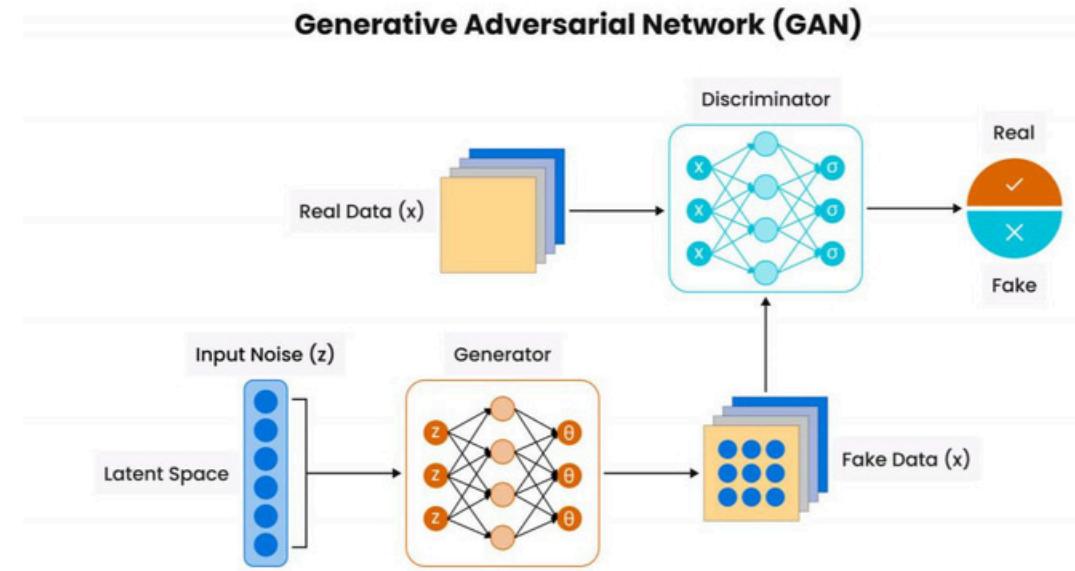
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# Problem statement

To generate realistic human face images using GANs and compare the performance of DCGAN and CGAN, where DCGAN generates images without control and CGAN generates images with attribute-based conditioning, in order to analyze which model produces more accurate and controlled results.

# GAN

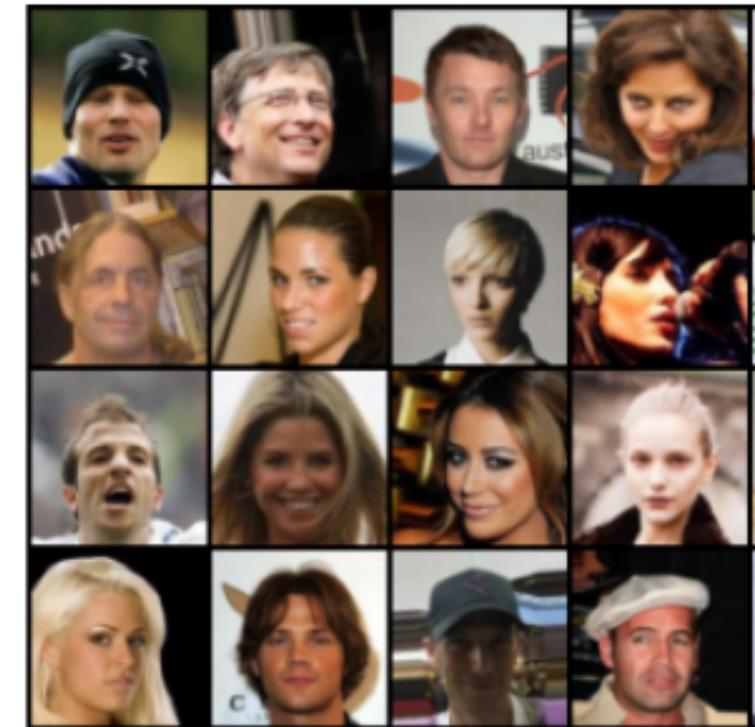
- Consists of two main parts:
  1. Generator—creates fake images from random noise.
  2. Discriminator – distinguishes real images from fake ones.
- Both are trained together in a competitive process (adversarial learning).
- Goal: Generator improves until fake images look indistinguishable from real ones.
- Widely used in face generation, image synthesis, and creative AI applications.



# Dataset

## CELEBA

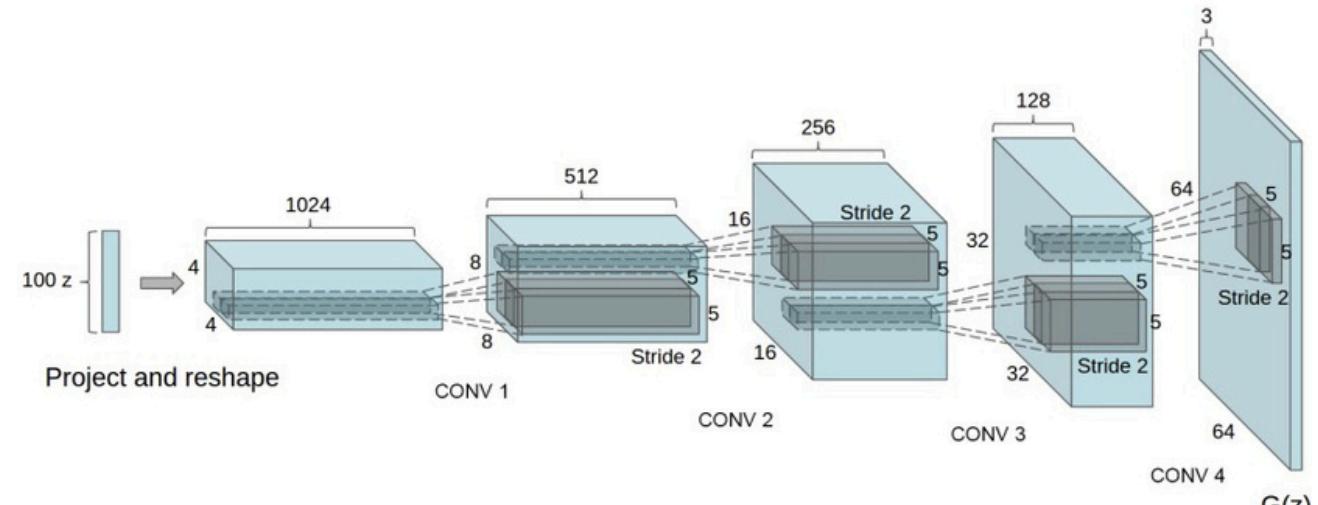
- **Full Name:** CelebFacesAttributes Dataset (CelebA)
- **Content:** Over **20,000 celebrity images** with **40 attribute labels** per image (e.g., smiling, male/female, glasses, hair color).
- **Image Size:** Original images are **178×218 pixels**, commonly resized for training.
- **Use in Face Generation:**
- DCGAN uses images to learn **general face features**.
- cGAN uses **attribute labels** for controlled generation.



**Dataset Link -** <https://www.kaggle.com/datasets/jessicali9530/celeba-dataset/data>

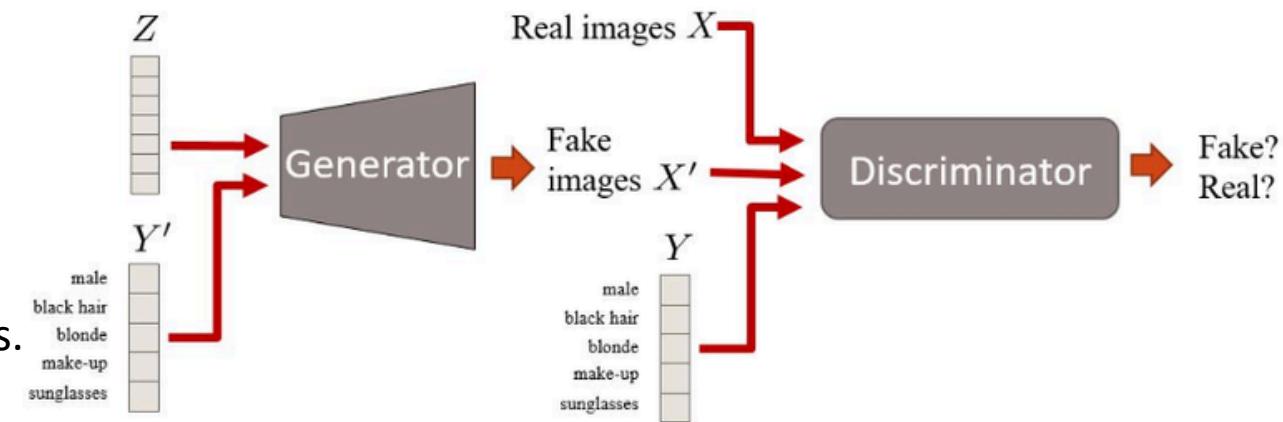
# DCGAN for Face Generation

- **Dataset used:** CelebA(large-scale celebrity face dataset).
- **Training process:**
  - Generator learns to create faces from random noise.
  - Discriminator learns to differentiate real celebrity faces from generated ones.
- **Progress during training:**
  - Early epochs → blurry or distorted faces.
  - Later epochs → clearer and more realistic human faces.
- **Output:** Synthetic faces that look similar to real people but do not actually exist.

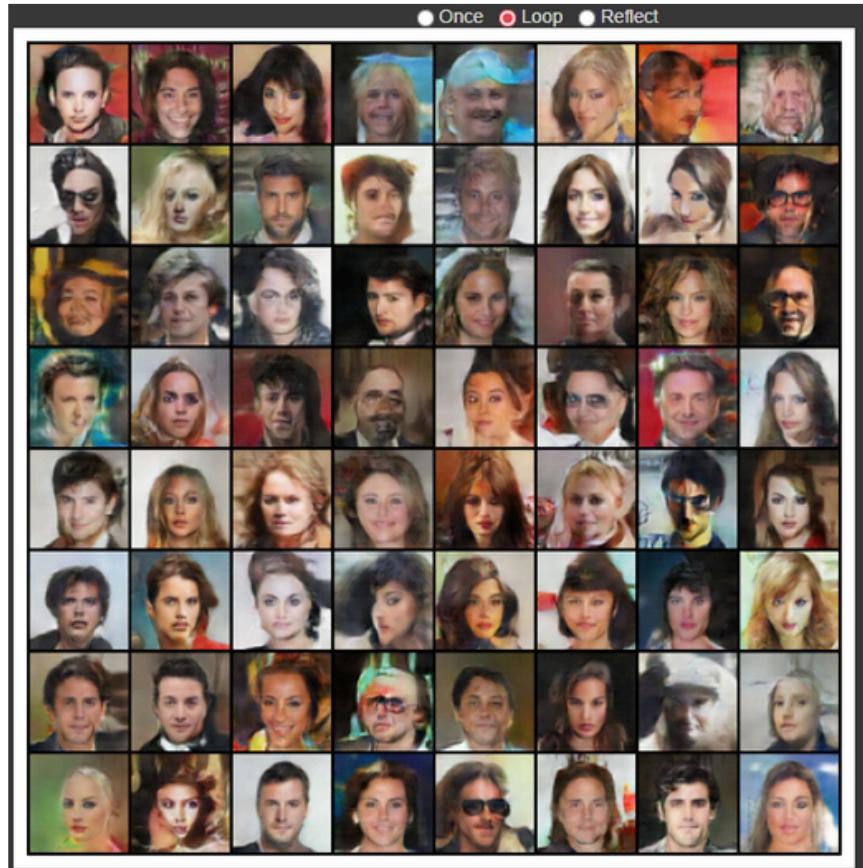


# CGAN for Face Generation

- **Dataset used:** CelebA with attribute labels (e.g., smiling, male/female, glasses, hair color).  
**Generator** produces faces that match a given attribute condition.
- **Examples of controlled generation:**
  - Generate a smiling face vs. non-smiling face.
  - Generate faces with or without glasses.
  - Control gender or hairstyle in generated faces.
- **Advantage:** Provides **fine-grained control** over the characteristics of generated faces.
- **Output:** More realistic and customizable faces compared to DCGAN.



# DCGAN VS CGAN Results



# CGAN vs DCGAN Result Comparison



Aspect	DCGAN	CGAN
Type	Unconditional GAN	Conditional GAN
Input	Noise vector only (zzz)	Noise vector + Label (z,yz, yz,y)
Control	No control (random outputs)	Controlled by labels (e.g., Male/Female)
Output in Project	Random faces (male/female mixed)	Gender-specific faces (Male/Female based on label)
Use Case	General face synthesis	Attribute-specific face synthesis
Final Training Loss	Loss_D: 0.4407, Loss_G: 2.3467	Loss_D: 1.6764, Loss_G: 5.3867
Discriminator Accuracy	$D(x) \approx 0.7783$	$D(x) \approx 0.9789$
Generator Fooling Ability	$D(G(z)) \approx 0.1389 / 0.1195$	$D(G) \approx 0.7493 / 0.0080$

# DCGAN VS CGAN

Features	DCGAN	cGAN
<b>Input</b>	Random noise	Noise + condition/label
<b>Output Control</b>	No control (random faces)	Controlled by attribute (e.g., smile, age)
<b>Applications</b>	General face generation	Attribute-specific face generation
<b>Flexibility</b>	Limited	High –user can choose desired features
<b>Output Quality</b>	Realistic faces	Realistic + customizable faces

# Challenges Faced

- **Mode collapse:** Generator produces limited variety of images.
- **Training instability:** GANs are difficult to train and need careful tuning.
- **High computational cost:** Requires large datasets and powerful GPUs.
- **Overfitting:** Generator may memorize training data instead of generalizing.
- **Evaluation difficulty:** Hard to measure image quality quantitatively.

# Ethical Considerations

**GDPR applies** (faces = biometric data)

## **Key Issues:**

- **Consent** – Use images only if collected with proper permission.
- **Privacy** – synthetic faces may resemble real people → misuse risk
- **Bias & Fairness** – Datasets may be unbalanced → biased results.
- **Misuse Risk** – deepfakes, identity fraud, misinformation

# Applications

- **AI Art & Avatars** – Create virtual characters for games, animation, and social media.
- **Deepfake Generation** – Realistic face swaps in videos (also raises ethical concerns).
- **Data Augmentation** – Generate synthetic faces to improve training datasets for ML models.
- **Entertainment & Gaming** – Realistic NPC faces, character design, virtual worlds.
- **Film & VFX Industry** – Generate extras, crowd simulations, or digital actors.
- **Research & Healthcare** – Facial feature synthesis for studies in psychology or medicine.

# Conclusion

GAN-based face generation has emerged as an effective technology for producing highly human faces from random noise. With models like DCGAN enhancing image quality and cGAN enabling controlled face generation based on attributes such as smiles, gender, or glasses, the technology has achieved remarkable progress. It offers higher-quality, controllable, and ethical AI-generated faces with wide applications in gaming, entertainment, AI art, and data augmentation. However, challenges such as training stability, mode collapse, and ethical concerns remain key obstacles. Looking ahead, future developments aim to address these limitations, making the technology increasingly impactful and responsible in its applications.

Thank You!!