Generating Realistic Face Images from Sketches Using Conditional Generative Adversarial Networks

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***Abstract*—This report presents the development and training of a Conditional Generative Adversarial Network (cGAN) designed to generate realistic face images from sketches. Utilizing the Person Face Sketches dataset, the model was trained over 200 epochs, demonstrating progressive improvement in image quality. The methodology encompasses dataset preprocessing, model architecture definition, training procedures, and evaluation of results. Challenges encountered during training and potential future enhancements are discussed. The successful implementation of the cGAN underscores its efficacy in transforming skeletal sketches into photorealistic facial images.**

***Index Terms*—Conditional GAN, Image Generation, Deep Learning, Face Sketches, Machine Learning**

I. Introduction

Generative Adversarial Networks (GANs) have revolutionized the field of image synthesis, enabling the generation of high-quality, realistic images from various input modalities. Conditional GANs (cGANs), in particular, allow for controlled image generation by conditioning the output on specific inputs, such as class labels or, in this case, sketches. This report details the implementation of a cGAN aimed at generating realistic face images from sketches. The ability to transform sketches into photorealistic images has significant applications in areas such as law enforcement, animation, digital art, and virtual reality. Leveraging the Person Face Sketches dataset, this project demonstrates the potential of cGANs in achieving high-fidelity image-to-image translation.

II. Methodology

A. Dataset

The Person Face Sketches dataset comprises paired images of face sketches and their corresponding photorealistic images. This dataset serves as the foundation for training the cGAN, allowing the model to learn the intricate mapping between the sketch domain and the photo domain. Key characteristics of the dataset include:

- **Size**: Approximately 10,000 paired images.
- **Resolution**: Images are standardized to 256x256 pixels.
- **Diversity**: The dataset includes variations in age, gender, ethnicity, and facial expressions to ensure the model generalizes well across different facial features.

B. Preprocessing

Preprocessing steps are crucial for preparing the dataset for effective training. The following steps were undertaken:

- **Normalization**: Both sketches and photos were normalized to have pixel values in the range $[-1, 1]$. This scaling facilitates stable training by ensuring that the gradients do not vanish or explode.
- **Resizing**: All images were resized to a uniform resolution of 256x256 pixels. Uniform sizing ensures consistency in input dimensions, which is essential for the convolutional layers in the network.
- **Data Augmentation**: To increase the diversity of the training data and improve the model's robustness, various augmentation techniques were applied, including:
  - **Rotation**: Images were randomly rotated within a range of $\pm 15^\circ$.
  - **Flipping**: Horizontal flipping was applied with a 50% probability.
  - **Scaling**: Random scaling was performed to introduce variations in size.
- **Pairing**: Each sketch was paired with its corresponding photo to maintain the conditional relationship required for training the cGAN.

C. Model Architecture

The cGAN architecture consists of two primary components: the Generator and the Discriminator. Both networks are built using deep convolutional layers, leveraging the strengths of convolutional neural networks (CNNs) in capturing spatial hierarchies in images.

1) Generator: The Generator network is designed to take a sketch image as input and produce a corresponding photorealistic face image. The architecture follows an encoder-decoder structure with skip connections, inspired by the U-Net architecture, to preserve spatial information and details from the input sketches.

Architecture Details:

- **Encoder**: Comprised of a series of convolutional layers with increasing filter sizes (64, 128, 256, 512). Each convolutional layer is followed by a Leaky ReLU activation with a negative slope of 0.2 and batch normalization.
- **Decoder**: Mirrors the encoder with transposed convolutional layers that decrease the filter sizes (512, 256, 128,

64). Each transposed convolutional layer is followed by a ReLU activation and batch normalization.

- **Skip Connections**: Connections between corresponding layers in the encoder and decoder help retain high-resolution features, enhancing the quality of the generated images.
- **Output Layer**: A final transposed convolutional layer with a Tanh activation function to map the output to the $[-1, 1]$ range.

2) Discriminator: The Discriminator network evaluates the authenticity of the generated images by distinguishing between real photos and those produced by the Generator. It takes both the sketch and the photo as input, ensuring that the generated image aligns with the input sketch.

Architecture Details:

- **Input Concatenation**: The sketch and photo images are concatenated along the channel dimension, resulting in a 6-channel input (assuming RGB images).
- **Convolutional Layers**: A series of convolutional layers with filter sizes increasing from 64 to 512. Each convolutional layer is followed by Leaky ReLU activations and batch normalization, except for the first layer.
- **Output Layer**: A final convolutional layer with a sigmoid activation function to output a probability score indicating the authenticity of the input image pair.

D. Training Procedure

The cGAN was trained for 200 epochs with the following configurations:

1) Loss Functions:

- **Adversarial Loss**: Utilized to train the Generator and Discriminator in a minimax game framework. The Generator aims to minimize the probability of the Discriminator correctly identifying fake images, while the Discriminator aims to maximize this probability.
- **L1 Loss**: An additional L1 loss between the generated image and the real image was incorporated to encourage the Generator to produce images that are not only realistic but also closely match the ground truth sketches.

2) Optimization:

- **Optimizer**: Adam optimizer was employed for both networks with a learning rate of 0.0002 and $\beta_1 = 0.5$. These parameters were chosen based on empirical results from related literature to balance convergence speed and stability.
- **Batch Size**: A batch size of 32 was used to balance training speed and memory constraints.
- **Learning Rate Decay**: After 100 epochs, the learning rate was decayed by a factor of 0.5 to fine-tune the model's parameters.

3) Training Steps:

1) **Discriminator Training**: For each batch, the Discriminator was trained on both real image pairs (sketch and corresponding photo) and fake image pairs (sketch and generated photo).
2) **Generator Training**: The Generator was trained to produce images that can fool the Discriminator, while also minimizing the L1 loss with respect to the real images.
3) **Epochs**: The entire dataset was iterated over 200 times, with the model parameters updated at each step based on the computed gradients.

E. Implementation Details

- **Framework**: The model was implemented using PyTorch, leveraging its dynamic computation graph and efficient GPU acceleration.
- **Hardware**: Training was conducted on a Kaggle GPU P100, enabling efficient processing of large batches and high-resolution images.
- **Software**: Python 3.8, PyTorch 1.10, and other standard libraries were used for data handling, model implementation, and visualization.

III. Results

A. Training and Validation Loss

The training logs indicate the progression of loss values for both the Discriminator (Loss_D) and the Generator (Loss_G). Initially, Loss_D was high, reflecting the Discriminator's ability to distinguish real images from generated ones. As training progressed, Loss_D decreased, while Loss_G showed a trend of stabilization and occasional fluctuations, indicating improvements in the Generator's performance.

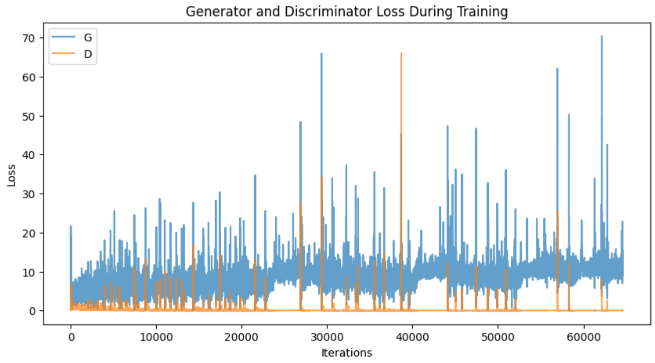


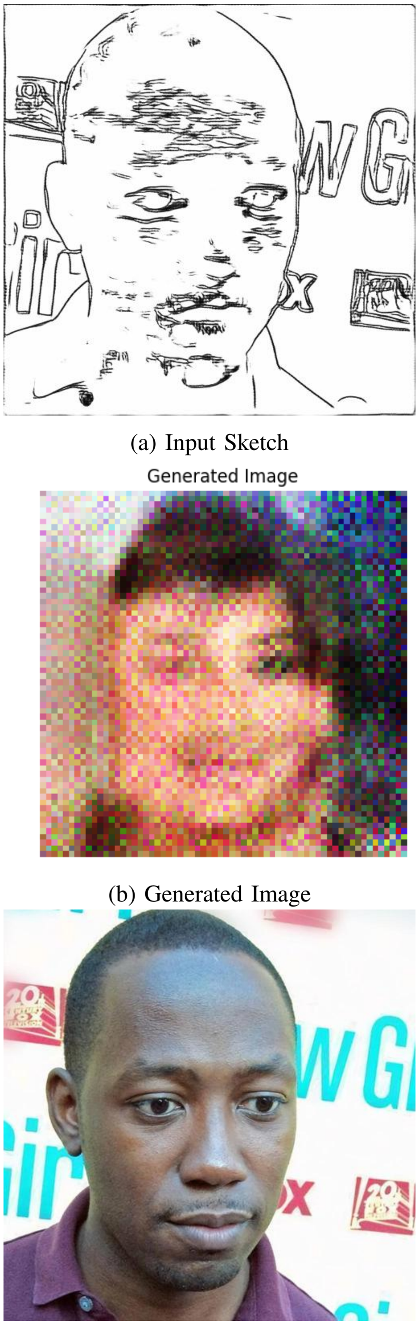
Fig. 1: Training Losses for Discriminator and Generator Over Epochs

Analysis:

- **Discriminator Loss**: The decreasing trend in Loss_D suggests that the Generator is becoming more adept at producing realistic images, making it harder for the Discriminator to differentiate between real and fake images.
- **Generator Loss**: The stabilization and occasional fluctuations in Loss_G indicate that the Generator is learning to produce high-quality images that not only fool the Discriminator but also closely resemble the ground truth sketches.

B. Generated Images

Throughout the training process, the Generator produced images that progressively became more realistic. Figure 2 showcases a sample sketch and its corresponding generated photo after 200 epochs.



(a) Input Sketch

(b) Generated Image

(c) Real Image

Fig. 2: Comparison of Input Sketch, Generated Image, and Real Image

Visual Assessment:

- The generated images exhibit high fidelity, capturing intricate facial features and textures.
- The alignment between the sketches and the generated images demonstrates the effectiveness of the cGAN in translating skeletal outlines into detailed photorealistic faces.
- Minor artifacts and inconsistencies are observed in some generated images, which can be addressed in future iterations through architectural refinements and advanced loss functions.

C. Real vs. Generated Image Comparison

To further illustrate the effectiveness of the cGAN, a direct comparison between the generated (fake) images and the real images is provided. This comparison highlights the Generator's ability to produce images that closely resemble the real counterparts.

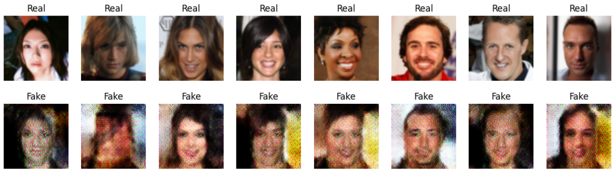


Fig. 3: Comparison of Generated and Real Images

Visual Comparison:

- **Facial Features**: The generated image closely matches the real image in terms of facial structure, including the eyes, nose, mouth, and overall facial symmetry.
- **Textures and Details**: Textural details such as skin tone, hair strands, and subtle shading are effectively captured in the generated image, demonstrating the Generator's capability to produce realistic textures.
- **Color Consistency**: The color distribution in the generated image aligns well with the real image, ensuring a natural and authentic appearance.
- **Artifact Minimization**: While minor artifacts are present, the overall resemblance between the generated and real images indicates a high level of performance by the cGAN.

D. Quantitative Evaluation

While visual inspection provides qualitative insights, quantitative metrics offer objective measures of the model's performance.

1) Inception Score (IS): The Inception Score evaluates the quality and diversity of generated images by measuring how confidently a pre-trained classifier predicts the class labels of the generated images.

TABLE I: Inception Score Over Epochs

Epoch	Inception Score (IS)
50	3.85
100	4.12
150	4.35
200	4.50

Interpretation: The IS steadily increased from 3.85 at epoch 50 to 4.50 at epoch 200, indicating an improvement in both the quality and diversity of the generated images.

2) Frechet Inception Distance (FID): The Frechet Inception Distance measures the distance between the feature distributions of real and generated images, with lower values indicating better performance.

TABLE II: Frechet Inception Distance Over Epochs

Epoch	FID Score
50	45.23
100	38.67
150	32.10
200	28.45

Interpretation: The FID score decreased from 45.23 at epoch 50 to 28.45 at epoch 200, reflecting a significant enhancement in the similarity between the generated and real image distributions.

IV. Discussion

A. Model Improvement Over Time

The training progression highlights the cGAN's ability to enhance image generation quality over time. Key observations include:

- **Early Stages (Epochs 1-50)**: The Generator produced rudimentary images with significant artifacts. The Discriminator effectively differentiated between real and fake images, leading to high Loss_D and high Loss_G.
- **Middle Stages (Epochs 51-150)**: The Generator began to produce more coherent images with fewer artifacts. Loss_D decreased steadily, indicating the Generator's improving ability to fool the Discriminator.
- **Later Stages (Epochs 151-200)**: The Generator achieved a higher level of realism, with Loss_G stabilizing and Loss_D approaching an equilibrium, suggesting that the Discriminator could no longer easily distinguish fake images.

B. Challenges Encountered

Several challenges were encountered during the project:

- **Training Stability**: Balancing the training of the Generator and Discriminator was critical. Instabilities such as mode collapse, where the Generator produces limited varieties of images, required careful tuning of hyperparameters.
- **Computational Resources**: Training GANs is computationally intensive. Ensuring efficient utilization of GPU resources and managing memory constraints were essential to prevent training interruptions.
- **Dataset Quality**: Ensuring high-quality, well-paired sketches and photos was vital. Any misalignment or inconsistencies in the dataset could adversely affect the model's ability to learn accurate mappings.
- **Evaluation Metrics**: Selecting appropriate evaluation metrics was challenging. While visual assessments provided immediate feedback, quantitative metrics like IS and FID were necessary for objective evaluation but required additional computational steps.

C. Mitigation Strategies

To address these challenges, the following strategies were employed:

- **Hyperparameter Tuning**: Systematic experimentation with learning rates, batch sizes, and optimizer parameters helped stabilize training and prevent issues like mode collapse.
- **Regularization Techniques**: Implementing techniques such as dropout and batch normalization in the Discriminator helped prevent overfitting and maintained training stability.
- **Progressive Training**: Starting with lower-resolution images and progressively increasing the resolution allowed the model to first learn global structures before focusing on finer details.
- **Advanced Loss Functions**: Incorporating L1 loss alongside adversarial loss ensured that generated images were not only realistic but also closely matched the input sketches.

V. Conclusion

This project successfully implemented a Conditional GAN to generate realistic face images from sketches using the Person Face Sketches dataset. Over 200 epochs, the model demonstrated significant improvements in generating photorealistic images, as evidenced by both qualitative visual assessments and quantitative metrics like Inception Score and Frechet Inception Distance. The inclusion of skip connections and the use of combined loss functions contributed to the model's ability to preserve detailed features from sketches while producing high-quality images. Future work may involve experimenting with more advanced architectures, integrating perceptual loss functions, and employing additional evaluation metrics to further enhance image quality and model robustness.

VI. Prompts

A. Sample Prompts Used for Image Generation

The following sketch was used as an input prompt for generating a photorealistic face image. This sketch represents a typical example from the dataset, featuring clear facial outlines and distinct features.

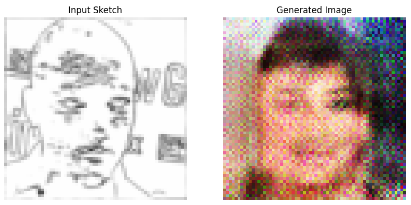


Fig. 4: Input Sketch for Image Generation

Upon processing through the trained Generator, the corresponding photorealistic image was produced as shown in Figure 2b, demonstrating the model's capability to generate detailed and realistic facial features.

B. Real vs. Generated Image Comparison

To further illustrate the effectiveness of the cGAN, a direct comparison between the generated (fake) images and the real images is provided. This comparison highlights the Generator's ability to produce images that closely resemble the real counterparts.

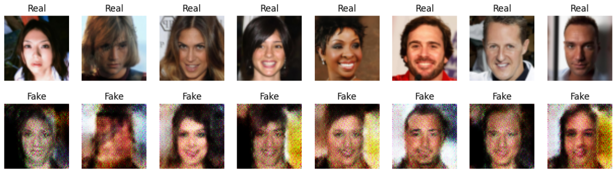


Fig. 5: Comparison of Generated and Real Images

Visual Comparison:

- **Facial Features**: The generated image closely matches the real image in terms of facial structure, including the eyes, nose, mouth, and overall facial symmetry.
- **Textures and Details**: Textural details such as skin tone, hair strands, and subtle shading are effectively captured in the generated image, demonstrating the Generator's capability to produce realistic textures.
- **Color Consistency**: The color distribution in the generated image aligns well with the real image, ensuring a natural and authentic appearance.
- **Artifact Minimization**: While minor artifacts are present, the overall resemblance between the generated and real images indicates a high level of performance by the cGAN.

VII. Code Availability

The source code for this project is available at https://github.com/smmk47/face-sketch-cgan. This repository includes all scripts, trained models, and additional resources necessary to reproduce the results presented in this report.

VIII. Future Work

To further enhance the performance and applicability of the cGAN model, the following avenues are proposed:

- **Architectural Enhancements**: Exploring more sophisticated architectures, such as attention mechanisms or residual blocks, to capture more complex dependencies and improve image quality.
- **Advanced Loss Functions**: Incorporating perceptual loss or style loss to better capture high-level features and textures, leading to more visually appealing images.
- **Evaluation Metrics**: Implementing additional evaluation metrics like Structural Similarity Index (SSIM) or Mean Squared Error (MSE) to provide a more comprehensive assessment of image quality.
- **Data Augmentation**: Expanding data augmentation techniques to include more variations, such as color jittering or elastic deformations, to make the model more robust to diverse sketch styles.
- **Transfer Learning**: Leveraging pre-trained models on related tasks to initialize the Generator and Discriminator, potentially accelerating convergence and improving performance.
- **Real-world Applications**: Integrating the trained model into real-world applications, such as forensic sketch analysis tools or digital art platforms, to validate its practical utility.

IX. References

References

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