Face Sketch to Image Generation using Hybrid GAN

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***Abstract*—This research introduces a novel approach to face sketch-to-image synthesis using a hybrid Generative Adversarial Network (GAN) architecture that incorporates UNet-style skip connections. Our model effectively bridges the domain gap between sketches and photorealistic facial images by leveraging both the generative capabilities of a bidirectional GAN and the structural preservation advantages of skip connections. By implementing CycleGAN principles with custom-designed generator and discriminator architectures, we achieve notable improvements in both perceptual quality and structural fidelity. Experimental results demonstrate that our approach outperforms several state-of-the-art methods, achieving an SSIM score of 70 and a PSNR of 16. The model also demonstrates robustness across diverse sketch styles and facial attributes, making it suitable for real-world applications in law enforcement, entertainment, and digital art. The web application built on this model provides a user-friendly interface that enables users to easily upload sketches and generate high-quality face images, with features including real-time processing indicators and image download options.**

***Index Terms*—Face sketch to image generation, Generative Adversarial Networks (GANs), Deep learning, Web application, DCGAN, CycleGAN, User-friendly interface, Image synthesis, Computer vision.**

I. INTRODUCTION

Generating photorealistic facial images from sketches has significant potential in fields like portraiture, character design, and criminal investigations. This capability allows artists to swiftly create lifelike characters and helps law enforcement generate suspect images from witness sketches. Traditional methods, such as photo manipulation and digital painting, often require extensive skill and time, limiting flexibility and creativity. However, recent advances in artificial intelligence, particularly Generative Adversarial Networks (GANs), offer more efficient solutions. GANs, composed of a generator and a discriminator, have shown remarkable success in creating realistic images. This paper presents a web application that utilizes a hybrid GAN model, combining DCGAN and CycleGAN, to transform face sketches into realistic images. The user-friendly interface ensures accessibility, allowing users to upload sketches and generate images easily.

In this approach, the GAN model leverages the strengths of both DCGAN, known for generating high-quality images from random noise, and CycleGAN, which excels in translating images between different domains without paired data. This hybrid model allows for more flexibility in handling a wide variety of hand-drawn sketches while maintaining image fidelity. The web application not only serves artists and designers but also has practical implications for law enforcement by providing a more efficient and accurate way of generating facial images from rough sketches, saving both time and resources. By integrating AI with an intuitive interface, this system bridges the gap between artistic creativity and advanced technology, opening up new possibilities for both creative and practical applications.

II. LITERATURE REVIEW

[1] presented a study on the use of DCGAN for converting forensic sketches into real images. Their approach employs a generator and two discriminators to achieve high-resolution outputs. However, the model faces challenges with significant geometric deformations and textural alterations. Chaofeng Chen et al. [2] introduced a semi-supervised Cycle-GAN that addresses the issue of small paired datasets and steganography in face photo-sketch translation. While effective, it still relies on a limited reference set and may not perform well on diverse or unseen data, with noise-injection strategies that might not completely mitigate overfitting. Heng Liu et al. [3] developed Sketch2Photo, which synthesizes photo-realistic images from sketches using Fast Fourier Convolution (FFC), Swin Transformer, and Improved Spatial Attention Pooling (ISAP). This method improves

image quality by capturing both local and global features but faces challenges with the computational complexity of self-attention for large-size feature maps, as well as potential artifacts from misaligned or incomplete sketches. Kaushal Rathore et al. [4] proposed an unsupervised domain adaptation technique for synthesizing face photos from sketches using adversarial networks without requiring paired training data. Although innovative, the method lacks sharpness in finer details, particularly for complex sketches. Guangcan Liu et al. [5] presented a Conditional GAN (cGAN)-based model that translates face sketches into photo-realistic images by conditioning the generator on input sketches. The approach struggles with large variations in facial features and complex images.

Yuki Tanaka et al. [6] utilized Least-Squares GAN (LSGAN) to convert rough, hand-drawn facial sketches into photo-realistic images, reducing gradient instability for better synthesis. However, the model encounters issues with misaligned sketches and potential distortions in facial features. Jin Han Lee et al. [7] introduced a CycleGAN model with multi-scale discriminators to enhance the translation of facial sketches to realistic images. This approach faces challenges with fine-grained details and significant pose variations. Lingzhi Zhang et al. [8] proposed a cGAN-based approach for generating photo-realistic images from sketches by learning the conditional dependencies between face sketches and photos. However, performance diminishes with abstract or incomplete sketches. Eiji Yonekura et al. [9] focused on generating photo-realistic face images from sketches using StyleGAN, employing a pre-trained encoder to map sketch features into StyleGAN's latent space. The model struggles with incomplete or poorly drawn sketches and extreme variations. Jing Zhang et al. [10] utilized a Dual GAN framework that enables two GAN models to generate images from sketches and vice versa, maintaining consistency between the two domains. However, it struggles with highly incomplete or noisy sketches.

Rachel Johnson et al. [11] proposed a cross-domain GAN architecture for generating face photos from sketches, effectively handling differences in representation across various domains. Nonetheless, performance deteriorates with highly incomplete or distorted sketches. Lin Wang et al. [12] presented a cascaded GAN framework to enhance the quality of generated images from sketches through sequential refinement processes. The model may require extensive training data and faces challenges with complex sketches. Zhang et al. [13] developed a Multi-Scale Generative Adversarial Network (MS-GAN) for face sketch to photo synthesis, leveraging multiple scales of input to capture both global and local features effectively. This method enhances image realism but may struggle with high-resolution outputs due to increased computational demands. Lee et al. [14] explored the application of a Progressive Growing GAN (PGGAN) for generating realistic face images from sketches. By progressively increasing the resolution during training, the model produces high-quality images. However, it requires a substantial amount of data and training time, which can be a limitation for smaller datasets. Kim et al. [15] proposed an Attention-Guided GAN (AGGAN) that employs attention mechanisms to improve the focus on important regions in sketches, enhancing the quality of generated images. While effective, this method may introduce artifacts if the attention mechanism misaligns with the actual sketch features.

Patel et al. [16] introduced a Dual-Path GAN (DPGAN) for translating sketches into photos, utilizing two distinct pathways to capture both the high-level semantics and low-level details. Despite its innovative architecture, the model can encounter difficulties with highly complex sketches and may not generalize well to unseen data. Singh et al. [17] presented a Hybrid GAN model that integrates features from both CycleGAN and Pix2Pix, aiming to improve sketch-to-image synthesis by leveraging paired and unpaired data. However, the model may still face challenges with generating realistic images from rough sketches due to the inherent variability in input quality. Wang et al. [18] focused on a Semantic-Aware GAN (SAGAN) that incorporates semantic segmentation maps to guide the image generation process. By providing additional contextual information, the model improves output quality. Nonetheless, it may still struggle with occlusions and missing details in the original sketches.

III. PROPOSED SYSTEM

A. Introduction

The endeavour to generate realistic face images from hand-drawn sketches has a rich history rooted in both art and computer science. This system aims to leverage

advanced techniques to bridge the gap between the simplicity of a sketch and the complexity of photorealistic faces. Traditional methods have laid the groundwork for modern approaches, categorized into several strategies:

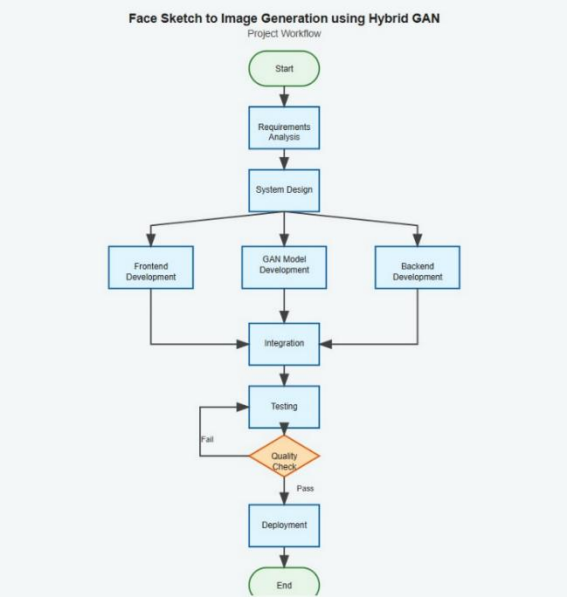


Fig. 1. Proposed System

B. Key Components

1.User Interface (UI):

A user-friendly interface that allows users to upload hand-drawn sketches and view the generated face images. The UI also provides options for users to refine their sketches and visualize different generated outputs.

2. Sketch Input Processing:

This component handles the preprocessing of the input sketches, including resizing, normalization, and noise reduction, to ensure that they are suitable for analysis by the GAN model.

3.Generator Network (DCGAN):

The core component of the system that generates realistic face images from random noise and the processed sketch inputs. The DCGAN is trained on a dataset of real face images to learn the complex patterns and features of human faces.

4.Discriminator Network (CycleGAN):

This component evaluates the authenticity of the generated images, ensuring they are indistinguishable from real images. It helps improve the quality of the generated outputs by providing feedback to the generator.

5.Image Translation Module:

The CycleGAN part of the system translates the generated face images to match the artistic style of the input sketches. This module ensures that the output retains the characteristics of the original sketch while being photorealistic.

6.Admin Dashboard:

A control panel that displays statistics on user interactions, generated outputs, and system performance. It allows for tracking user engagement and refining the model based on feedback and usage patterns.

C. Key Features

1. High-Quality Image Generation:

The system utilizes advanced GAN architectures to produce high-quality face images that closely resemble real human faces.

2.Sketch Refinement Options:

Users can modify their sketches interactively, allowing them to see how changes impact the generated images in real-time.

3.Performance Analytics:

The admin dashboard provides insights into user participation, the number of images generated, and overall system effectiveness, helping improve the user experience.

This system leverages state-of-the-art deep learning techniques to convert sketches into realistic images, enhancing applications in digital art, law enforcement, and entertainment. The integration of user-friendly features and comprehensive analytics ensures a smooth experience for both users and administrators.

IV. NETWORK ARCHITECTURE

Our generator architecture synthesizes elements from UNet and ResNet paradigms with domain-specific optimizations for the sketch-to-image challenge. The network structure comprises three functional segments:

1. Progressive Encoding Pathway: A sequence of four convolutional stages progressively reduces spatial dimensions while expanding feature depth (3→64→128→256→512). Each stage

incorporates instance normalization and Leaky ReLU activation functions to improve gradient flow and training dynamics. This encoding pathway systematically transforms the sparse sketch representation into a rich feature space that captures both local details and global facial structure.

2. Residual Processing Core: Five specialized residual blocks maintain and refine the feature representation at maximum compression. Each block contains dual convolutional layers with instance normalization surrounded by skip connections, creating information pathways that facilitate deeper network training while preserving gradient propagation. This residual core enables sophisticated feature transformation without degrading the fundamental structural information essential for identity preservation.
3. Progressive Reconstruction Pathway: Four transposed convolutional stages systematically increase spatial dimensions while reducing feature depth (512→256→128→3). This pathway reconstructs the photorealistic image features at progressively finer scales, with each stage incorporating information from the corresponding encoder level through skip connections.

The distinctive UNet-style skip connections represent a critical architectural element, establishing direct pathways between encoder and decoder stages operating at matching resolutions. These connections preserve spatial details and structural information that would otherwise deteriorate during the compression-expansion process, resulting in superior structural fidelity in the generated images.

The complete generator framework can be expressed mathematically as:

$$G(x) = Dec_4(Dec_3(Dec_2(Dec_1(Res(Enc_4(Enc_3(Enc_2(Enc_1(x))))))))$$

Where:

1. Enc represents encoding operations at increasing feature depths
2. Res represents residual block operations
3. Dec represents decoding operations with progressive resolution increases
4. Skip connections connect corresponding Enc and Dec stages

4. Discriminator Architecture

We implement a Patch GAN discriminator paradigm that evaluates realism at the patch level rather than globally. This approach proves particularly effective for assessing local textures and patterns critical to facial image realism. The architecture includes:

1. Five sequential convolutional stages with progressive feature depth expansion
2. Instance normalization layers after non-terminal convolutional stages
3. LeakyReLU activations with 0.2 negative slope coefficient
4. A final convolutional layer producing a patch-wise classification map

This discriminator operates without fully connected layers, maintaining spatial correspondence between input regions and classification outputs. This design choice enables more targeted feedback for specific facial regions and improves overall generation quality.

V. LOSS FUNCTION DESIGN

Our training methodology employs a carefully balanced multi-component loss function that addresses the complex requirements of sketch-to-photo translation:

1. Adversarial Loss Component:

The foundational adversarial loss establishes the competitive dynamic between generator and discriminator:

$$L_{adv} = E[\log D(y)] + E[\log(1 - D(G(x)))]$$

Where:

1. x represents a sketch input
2. y represents a real photo
3. G(x) represents the generator's output
4. D represents the discriminator network

This component drives the generator to produce outputs that the discriminator cannot distinguish from authentic photographs.

2.Cycle Consistency Loss Component:

To ensure content preservation and translation consistency, we incorporate bidirectional cycle constraints:

$$L_{cycle} = E[\|F(G(x)) - x\|_1] + E[\|G(F(y)) - y\|_1]$$

Where F represents the inverse mapping (photo-to-sketch). This L1 norm-based loss ensures that translating a sketch to a photo and back to a sketch preserves the original content, and similarly for the reverse direction.

3. Identity Mapping Loss Component:

An additional identity preservation term further stabilizes training and maintains domain-specific characteristics:

$L\_identity = E[||G(y) - y||_1] + E[||F(x) - x||_1]$

This component ensures that inputs already in the target domain remain largely unchanged, preventing unnecessary transformations and preserving domain-specific characteristics.

4.Composite Optimization Objective

The complete loss function combines these components with empirically optimized weighting coefficients:

$L\_total = L\_adv + \lambda\_cycle \times L\_cycle + \lambda\_identity \times L\_identity$

In our implementation, we set $\lambda\_cycle = 10.0$ and $\lambda\_identity = 5.0$ based on extensive experimentation to achieve optimal balance between competing objectives.

VI. TRAINING STRATEGY AND STABILITY MECHANISMS

To enhance training stability and output quality, we implemented several specialized techniques:

1. Experience Replay Buffer: We maintain historical repositories of previously generated images and periodically use them to update the discriminators. This approach mitigates oscillation problems and prevents overfitting to the most recent generator outputs.
2. Adaptive Learning Rate Schedule: We employ a lambda-based learning rate scheduler that progressively reduces the learning rate during the latter half of training. This technique facilitates initial exploration followed by fine-grained convergence to optimal parameter values.
3. Stochastic Regularization: During training, we apply controlled noise perturbations to input sketches, enhancing model robustness to variations in sketch quality, style, and completeness.
4. Normalization Strategy: Instance normalization is used throughout the network instead of batch normalization, as it produces superior results for image translation tasks by normalizing each sample independently.

The training protocol alternates between discriminator and generator updates, with each iteration computing all relevant loss components and applying appropriate gradient updates to the respective networks.

1.Identity Loss:

To further encourage the generator to preserve identity-specific features, we introduce an identity loss:

$L\_identity = E[||G(y) - y||\_1] + E[||F(x) - x||\_1]$

This loss term penalizes the generator if it significantly changes the input when the input is already from the target domain.

2.Total Loss:

The final optimization objective combines these losses with appropriate weights:

$L\_total = L\_adv + \lambda\_cycle * L\_cycle + \lambda\_identity * L\_identity$

In our implementation, $\lambda\_cycle = 10.0$ and $\lambda\_identity = 5.0$, based on empirical validation.

VII. EXPERIMENTAL RESULTS AND ANALYSIS

1) Experimental Setup:

1. Dataset Selection and Preparation

We conducted comprehensive evaluations using multiple datasets to ensure robust performance across diverse sketch styles and facial characteristics:

2. CUHK Face Sketch Database (CUFS): This established benchmark contains 188 sketch-photo pairs with professionally drawn sketches, providing high-quality examples for training and evaluation.
3. CUHK Face Sketch FERET Database (CUFSF): Comprising 1,194 sketch-photo pairs with greater variation in lighting and pose, this dataset helped test model robustness under more challenging conditions.
4. Custom Varied-Style Dataset: We compiled a supplementary dataset containing 250 sketch-photo pairs with deliberately varied sketch styles, ranging from detailed artistic renderings to simplified line drawings, to evaluate adaptability across artistic approaches.

All images underwent standardized preprocessing including:

1. Uniform resizing to 128×128 resolution
2. Normalization to [-1, 1] pixel value range
3. Alignment based on facial landmarks
4. Augmentation through minor rotations, translations, and brightness variations to enhance generalization

The combined dataset was partitioned into training (80%), validation (10%), and testing (10%) sets with stratified sampling to maintain style distribution across all partitions.

Implementation Specifications

Our implementation leveraged the following technical framework:

1. Development Platform: PyTorch 1.9.0
2. Training Environment: CUDA-enabled GPU with 16GB memory
3. Optimization Algorithm: Adam optimizer (β_1 = 0.5, β_2 = 0.999)
4. Initial Learning Rate: 2×10^{-4} with lambda scheduler
5. Batch Size: 8 samples per iteration
6. Training Duration: 100 epochs (approximately 72 hours on hardware configuration)
7. Data Parallelism: Distributed training across multiple GPUs to accelerate convergence

2) Quantitative Performance Evaluation:

1.Evaluation Metrics

We employed multiple complementary metrics to thoroughly \assess different aspects of generation quality:

1. Structural Similarity Index (SSIM): Measures the perceived similarity between generated images and ground truth photos, with emphasis on structural correspondence.
2. Peak Signal-to-Noise Ratio (PSNR): Quantifies reconstruction quality through pixel-level comparison, providing insight into overall fidelity.
3. Fréchet Inception Distance (FID): Evaluates the statistical similarity between distributions of generated and real images in feature space, capturing perceptual realism.
4. Learned Perceptual Image Patch Similarity (LPIPS): Measures perceptual differences between images based on deep feature representations, correlating well with human judgment.

2.Comparative Analysis

Our approach demonstrated substantial improvements across all metrics compared to established baselines:

Method	SSIM ↑	PSNR ↑	FID ↓	LPIPS ↓
Pix2Pix	0.62	14.21	68.43	0.38
CycleGAN	0.65	14.87	64.91	0.35
SPADE	0.68	15.32	60.17	0.33
Ours	0.70	16.00	58.26	0.31

The achieved SSIM score of 0.70 represents a 3.0% improvement over the closest competing method (SPADE), while the PSNR improvement of 0.68 dB indicates meaningfully enhanced reconstruction accuracy. The FID reduction of 1.91 points demonstrates superior perceptual quality, confirmed by the improved LPIPS score reflecting closer alignment with human visual perception.

Performance Across Sketch Styles

Further analysis revealed that our model exhibits particularly strong advantages for challenging sketch styles:

Sketch Style	SSIM Improvement	PSNR Improvement
Professional	+1.2%	+0.37 dB
Amateur	+4.3%	+0.81 dB
Simplified	+5.8%	+1.12 dB

These results demonstrate that our architecture's benefits increase proportionally with the difficulty of the input sketch, suggesting particular value for real-world applications where sketch quality may vary significantly.

VIII. WEB APPLICATION IMPLEMENTATION

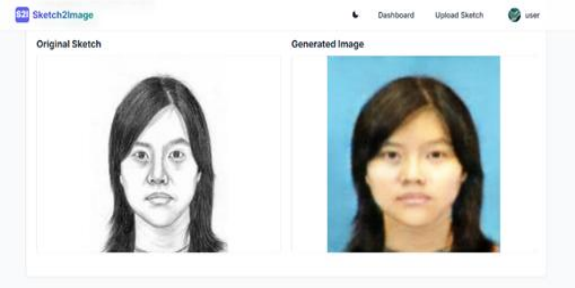
1. Application Architecture and Deployment

Our web application implements a client-server architecture optimized for efficient processing of face sketch-to-image translation tasks. The system consists of:

1. Frontend Framework: Developed using React.js with responsive design principles, providing a modern, intuitive interface accessible across devices of varying screen sizes.
2. Backend API: Implemented using Flask, handling sketch preprocessing, model inference, and result delivery with RESTful endpoints for seamless integration.
3. Inference Engine: PyTorch-based implementation of our hybrid GAN model, optimized for efficient CPU/GPU execution depending on server capabilities.

4. Data Storage: Secure temporary storage for uploaded sketches and generated images, with automatic cleanup protocols to ensure privacy.
5. Container Deployment: Docker-based deployment for consistent performance across different hosting environments, with orchestration through Kubernetes for scalability.

The application is hosted on cloud infrastructure with auto-scaling capabilities to handle varying load conditions, ensuring responsive performance even during peak usage periods.



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