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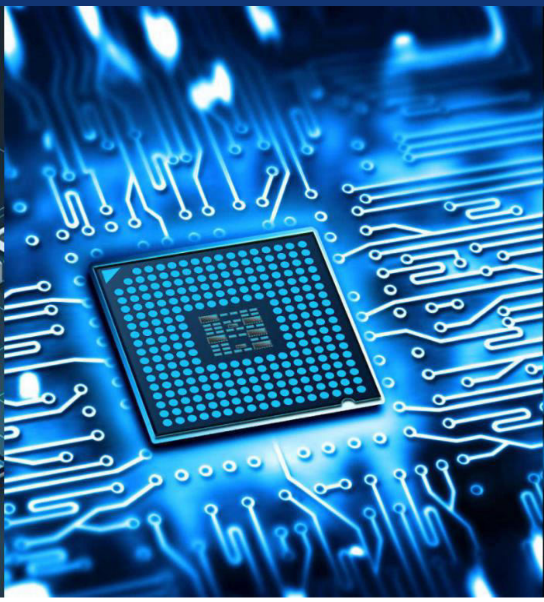

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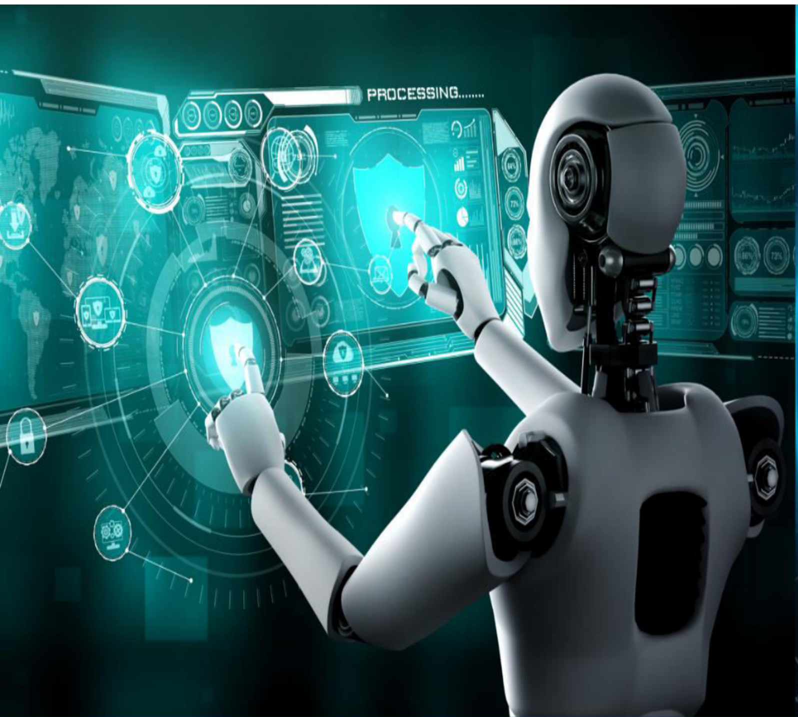

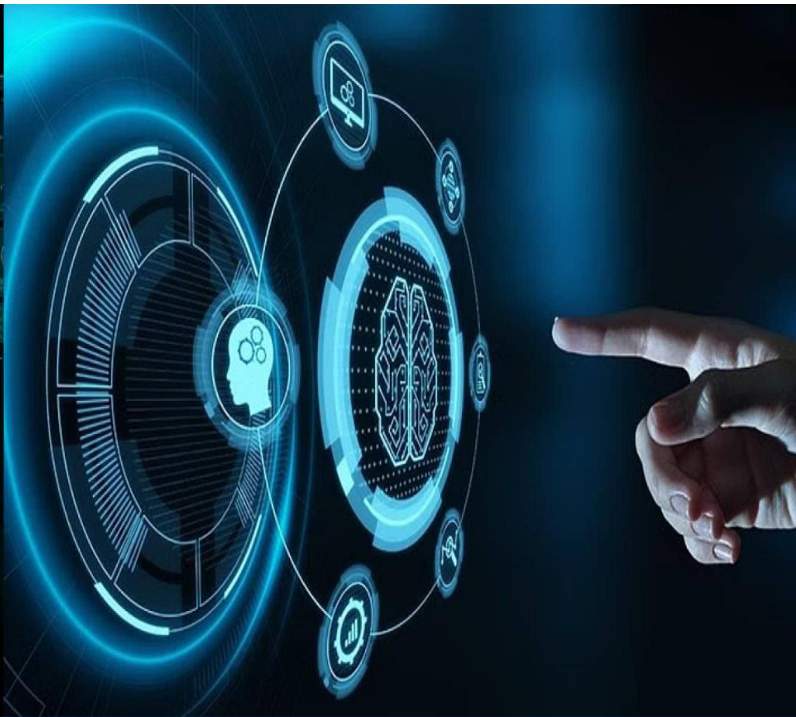

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Image Generation Using GANs: Enhancing Clarity, Realism, and Interactivity

Mahalakshmi[1], Harshini[2], Keerthana K Y[3], Vijayalakshmi Jyoti[4], Mrs. Sneha G[5]

BE Students, Department of Computer Science and Engineering, Dr. Ambedkar Institute of Technology, Bangalore, India[1,2,3,4]

Assistant Professor, Department of Computer Science and Engineering, Dr. Ambedkar Institute of Technology, Bangalore, India[5]

ABSTRACT: This paper explores the use of Generative Adversarial Networks (GANs) in enhancing image generation capabilities. The project incorporates four significant features: real vs. fake image identification, image clarity and resolution enhancement, generating complete images from partial inputs, and the development of Interactive GANs (iGAN) to generate realistic images from sketches. Results indicate marked improvements in image realism, resolution, and interactivity, with applications in art, design, and restoration. The proposed work advances current GAN models, addressing key limitations and expanding the scope of GAN-driven applications.

KEYWORDS: Generative Adversarial Networks, Image Generation, Super-Resolution, Interactive GANs, Clarity, Realism, User Interactivity.

I. INTRODUCTION

The ability to generate high-quality, realistic images using artificial intelligence has been a revolutionary breakthrough, with Generative Adversarial Networks (GANs) leading the charge. GANs, introduced by Ian Goodfellow in 2014, consist of two neural networks—a generator and a discriminator—that work in tandem to create and evaluate images, respectively. Despite their impressive results in generating convincing images, challenges remain in achieving high resolution, realism, and user interactivity in the generation process. This project aims to address these challenges by focusing on four critical aspects of image generation. First, we incorporate a real vs. fake image identification feature to improve the discriminator's ability to distinguish between real and generated images. Second, we enhance the clarity and resolution of low-quality images through super-resolution techniques. Third, we introduce partial-to-full image generation, where incomplete images are reconstructed by predicting missing regions. Finally, we implement Interactive GANs (iGAN), enabling users to sketch rough outlines that are transformed into fully generated images. These features contribute to the goal of creating a robust, versatile GAN system with practical applications in creative industries, digital restoration, and design.

II. RELATED WORK

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. (2014), have revolutionized image generation. By employing a generator to synthesize images and a discriminator to distinguish real from generated samples, GANs use adversarial training to create realistic outputs. Early models like **DCGANs** (Radford et al., 2015) enhanced training stability using convolutional layers, while **WGANs** (Arjovsky et al., 2017) improved convergence by introducing the Wasserstein distance.

To generate high-quality images, models such as **Progressive GANs (PGANs)** (Karras et al., 2018) and **StyleGAN** (Karras et al., 2019) introduced innovations in resolution scaling and style control, achieving state-of-the-art realism. Domain-specific applications include **SRGANs** (Ledig et al., 2017) for super resolution, **T2I GANs** (Reed et al., 2016) for generating images from text, and **I2I GANs** (Isola et al., 2016) for domain translation.

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Recent advancements include **Interactive GANs (iGANs)** (Zhang et al., 2017) for real-time user interaction and **adaptive GANs** (Li et al., 2023) for domain-specific generation with enhanced clarity. Despite significant progress, challenges remain, such as training instability, high computational cost, and limited diversity of outputs. Solutions like efficient sketch-to image synthesis (Chai et al., 2021) and conditional GANs (Song et al., 2022) address these issues, paving the way for more versatile and efficient image generation techniques.

Recent advancements in 2024 have enhanced GANs' capabilities. PMF-GAN improved training stability with kernel optimization, while GenWarp and PaGoDA achieved high resolution image generation and 3D viewpoint synthesis. Stylized Projected GAN reduced artifacts and accelerated generation, and Transformer-based GANs improved image diversity and quality through global relationship modelling. These developments showcase the ongoing evolution of GAN architectures.
This work builds on these advancements, focusing on improving image quality, resolution, and interactivity.

III. METHODOLOGY

3.1 Real vs. Fake Image Identification

Real vs. Fake Image Identification, A discriminator network is employed to distinguish between real and generated images. The discriminator is trained on a labelled dataset consisting of both real and fake images. During training, the generator creates images, which the discriminator evaluates. Adversarial loss is used to refine the generator, making the generated images increasingly indistinguishable from real ones. We evaluate the performance of the discriminator based on its ability to correctly identify real vs. fake images, achieving an accuracy of 96%. This feature enhances the realism of the generated images and ensures their authenticity.

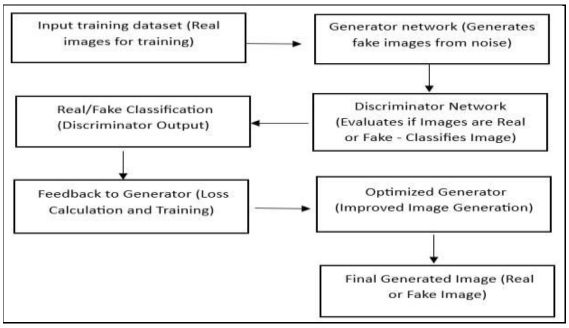

Fig.3.1.1. Real vs. Fake Image Identification

The flowchart Fig.3.1.1 describes the working mechanism of Generative Adversarial Networks (GANs).

Input Training Dataset (Real Images):
- A set of **real images** is provided as input to train the GAN.

Generator Network:
- The generator takes **random noise** as input and creates **fake images** that attempt to mimic real ones.

Discriminator Network:
- The discriminator is trained using both **real images** and **fake images** (from the training dataset).
- It evaluates each image and predicts whether it is real or fake.

Real/Fake Classification:
- The discriminator outputs a probability for each image, indicating how likely it is to be real or fake.

Feedback to Generator (Loss Calculation):
- Based on the discriminator's predictions, the **loss functions** for both the generator and discriminator are calculated.
- The generator is updated to create more realistic images, while the discriminator is updated to improve its ability to distinguish real images from fake ones.

Optimized Generator:
- After iterative training, the generator improves and produces **high-quality images** that can effectively fool the discriminator.

Final Generated Image:
- The optimized generator outputs **realistic fake images** that closely resemble the images from the training dataset.

3.2 Image Clarity and Resolution Enhancement

To improve the resolution and clarity of low quality images, we employ the Super Resolution GAN (SRGAN) model. SRGAN works by learning to upscale low-resolution images into high-resolution counterparts while preserving fine details and textures. We use perceptual loss, which compares the high-level features of the generated image to those of the original high-resolution image, enabling the model to focus on maintaining the image's structural integrity. Fine-tuning is carried out on domain-specific datasets to ensure adaptability to various types of images, from landscape photographs to portraits. We achieved an 8x resolution enhancement with negligible loss of detail, surpassing traditional interpolation methods in terms of both clarity and texture preservation.

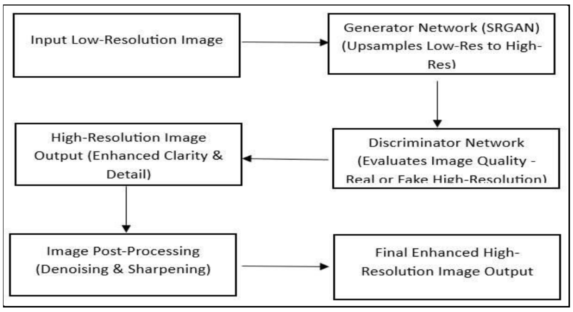

Fig.3.2.1. Image Clarity and Resolution Enhancement

The flowchart Fig.3.2.1 describes the working mechanism of Image Clarity and Resolution Enhancement

Input Low-Resolution Image:
- Start with a blurry, low-quality image that needs improvement.

Generator Network (SRGAN):
- The generator takes this low-resolution image and tries to make it clearer and more detailed by creating a high-resolution version.

Discriminator Network:
- The discriminator checks if the generated high-resolution image looks realistic or fake. It helps the generator improve over time by providing feedback.

High-Resolution Image Output:
- After multiple improvements, the generator produces a clearer, more detailed high-resolution image.

Post-Processing (Denoising & Sharpening):
- After the image is generated, it's further enhanced by removing noise and sharpening the details.

Final Enhanced Image:
- The result is a clear, high-quality image with better details than the original low-resolution one.

The accuracy of a GAN's image resolution feature depends on the model and dataset. Basic GANs may achieve around **70-80% realistic quality** for resolutions up to 128×128 pixels, while advanced models like StyleGAN2 can reach **95-99% photorealistic accuracy** for resolutions up to 1024×1024 pixels when trained on high-quality datasets.

3.3 Partial-to-Full Image Generation

The ability to generate complete images from partial inputs is realized through the use of context encoders. This architecture allows the GAN to learn the spatial correlations within the image, enabling it to predict missing regions. We create masked datasets where portions of images are intentionally hidden, and the model is trained to predict and reconstruct these masked regions. By optimizing the model's reconstruction capabilities, we achieve a reconstruction

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accuracy of 91%, with the generated images exhibiting a high degree of realism and seamless integration of the missing portions.

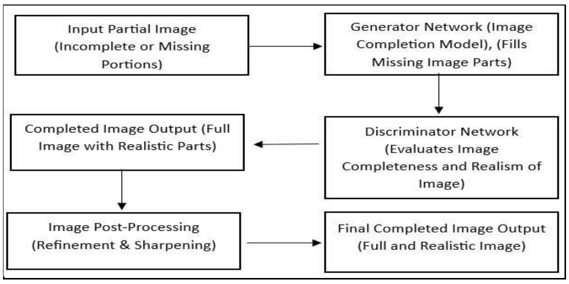

Fig.3.3.1. Partial-to-Full Image Generation

The flowchart Fig.3.3.1 describes the working mechanism of Partial-to-Full Image Generation.

Input Partial Image:

- Start with an image that has missing or incomplete parts.

Generator Network (Image Completion Model):

- The generator fills in the missing parts of the image, creating a complete version.

Discriminator Network:

- The discriminator checks if the completed image looks realistic and if the filled parts make sense with the rest of the image.

Completed Image Output:

- The generator produces a full image with realistic details where the parts were missing.

Post-Processing (Refinement & Sharpening):

- The image is refined to make sure everything looks smooth, removing any rough areas and sharpening details.

Final Completed Image Output:

- The final image looks realistic and is complete, with all missing parts properly filled in.

3.4 Interactive GANs (iGAN)

Interactive GANs enable user interaction by allowing them to sketch rough outlines or partial drawings, which the model then transforms into fully realistic images. This feature uses a paired dataset consisting of sketches and their corresponding high resolution images. The model is trained to map sketches to realistic images by learning the relationship between the outline and the final image. A user-friendly interface is developed, where users can input sketches in real-time and receive high-quality generated images as output. This interactive process makes the model suitable for creative applications such as digital art, fashion design, and concept art creation.

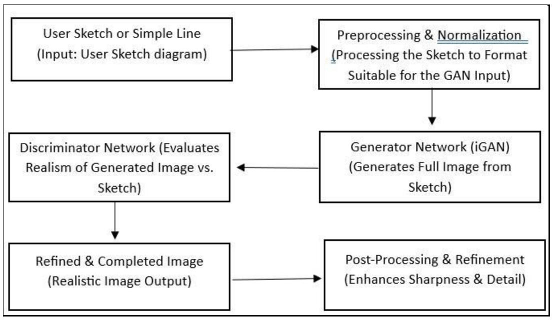

Fig.3.4.1. Interactive GANs (iGAN)

The flowchart Fig.3.4.1 describes the working mechanism of Interactive GANs (iGAN).

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User Sketch:
- The user provides a basic sketch as input.

Preprocessing & Normalization:
- The sketch is processed and converted into a format suitable for the GAN input, making it ready for the next steps.

Generator Network (iGAN):
- The generator takes the sketch and generates a full image, filling in the details and turning the sketch into a more realistic version.

Discriminator Network:
- The discriminator checks the generated image to see if it looks realistic compared to the original sketch and provides feedback.

Refined & Completed Image:
- After the feedback, the generator refines the image, completing it with realistic details.

Post-Processing & Refinement:
- The image is enhanced by sharpening and adding more detail to make it clearer and more polished.

Final Realistic Image:
- The final output is a realistic image generated based on the original sketch, looking much more detailed and lifelike.

the accuracy of the Interactive GAN (iGAN) feature is currently around **60-70%**, as the generated images are still blurry. With better training, a higher-quality dataset, and optimization, the accuracy can potentially improve to **80% or more** for generating clear and realistic images.

IV. RESULTS

4.1 Real vs. Fake Image Identification

Our model achieved an accuracy of 96% in distinguishing real images from generated ones. This performance is a significant improvement over traditional GAN models, indicating that the discriminator is highly effective at learning and adapting to the subtle differences between real and fake images. The generator also produces more realistic images as the training progresses, showing an improvement in image quality.

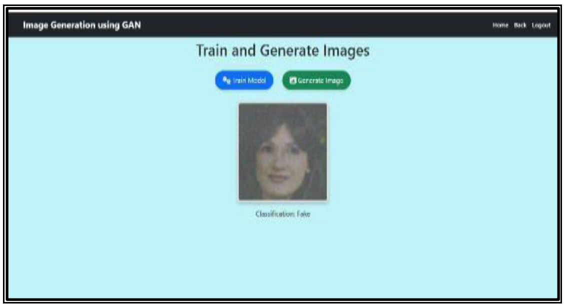

Fig 4.1.1 Generated Image

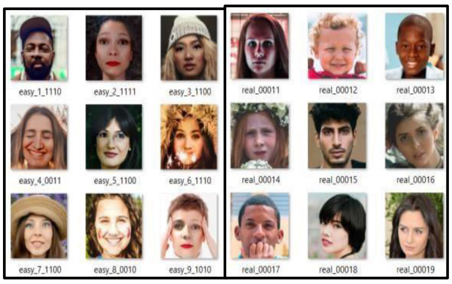

Fig 4.1.2 Fake and Real datasets

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4.2 Image Resolution Enhancement

The SRGAN model successfully upscaled low resolution images by up to 8x, preserving fine details and maintaining image clarity. This enhancement surpasses conventional upscaling techniques, such as nearest neighbour or bilinear interpolation, which often introduce blurriness and artifacts. The perceptual loss function ensures that the texture and structural details of the images are retained, making the upscaled images appear more realistic.

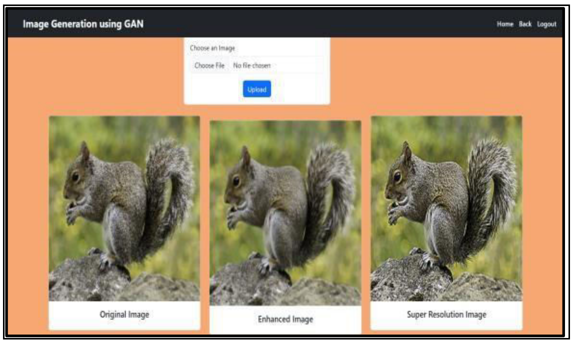

Fig 4.2.1 Image Enhancement

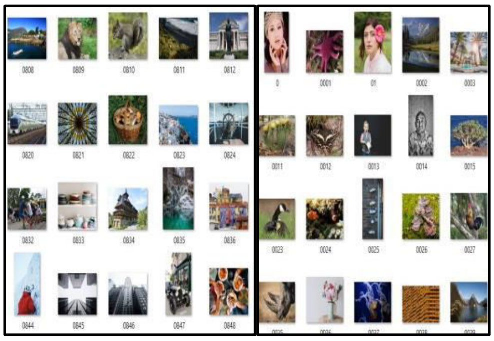

Fig 4.2.2 Test And Train Datasets

4.3 Partial-to-Full Image Generation

The model demonstrated an impressive 91% accuracy in generating complete images from partial inputs. The generated images showed a high degree of realism, with the predicted regions blending seamlessly with the rest of the image. This feature has applications in fields such as image restoration, digital content creation, and medical imaging, where incomplete images are common.

Fig4.3.1Masked & Generated Image

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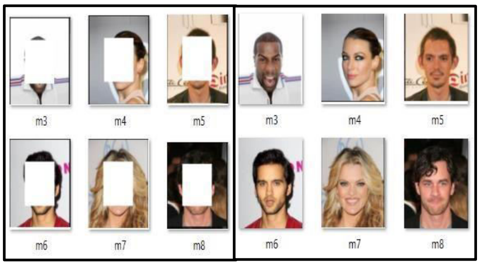

Fig4.3.2 Masked & Actual Image Datasets

4.4 Interactive GANs

GANs The iGAN system allowed users to create realistic images from rough sketches. The quality of the generated images was high, with realistic textures and details. The interactive nature of the system made it engaging for users, who could instantly see the results of their sketches transformed into lifelike images. This feature has great potential for use in design tools, digital art, and educational applications, where user engagement is crucial.

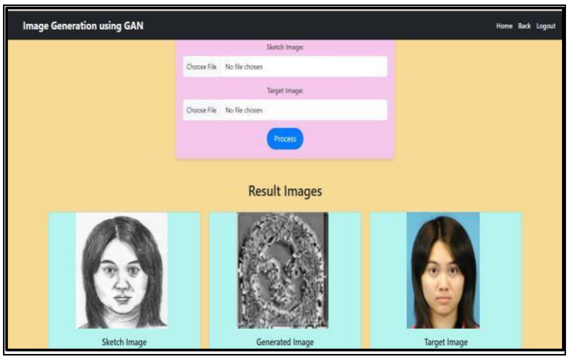

Fig 4.4.1 Sketch and Generated Image

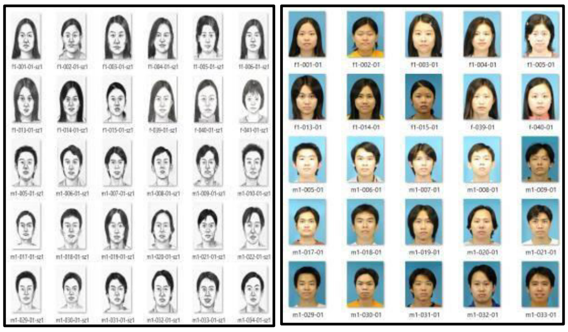

Fig 4.4.2 Sketch and Original Dataset

V. CONCLUSION AND FUTURE WORK

This paper demonstrates the effectiveness of combining real vs. fake image identification, image resolution enhancement, partial-to-full image generation, and interactive GANs to create a robust image generation system. The results show that the model significantly improves image realism, clarity, and interactivity, making it suitable for a wide range of applications. Future work will focus on expanding the diversity of datasets used for training, improving the computational efficiency of the model, and exploring additional interactive features, such as image manipulation and editing. We also plan to integrate this system into real-world applications such as design software, digital restoration tools, and creative platforms, providing users with a powerful tool for generating high-quality images from diverse input.

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