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Literature Survey on Indian Historical Image Reconstruction Using GAN

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Abstract: *GANs have emerged as one of the most promising deep learning frameworks for generating realistic images. a neural network called the generator competes with another neural network ,known as the discriminator, in a minimax games, thus, GAN learns to synthetics high fidelity images indistinguishable from the ground trough . the generator synthesizes images with a random noise vector while the descriminator evaluates the generated samples against the real ones by providing loses to drive the generated to improve iterativly . this adversarial paradiagm allows GANS to capture complex data distribution s and generated new, photosynthetic output . Apllications of GANs based image generations span s wide range of fields ,from artidtics creation and medical imaging to data augmentation and computer graphics. While some of these challenges, such as training instability, mode collapse, and computational costs, remain under active research, continuous advancement of GAN architectures and optimization techniques has the potential to further boost their performance in generating diverse, high-quality, controllable images, and further establish GANs as the cornerstone of modern generative modelling.*

Keywords: *GANs*

I. INTRODUCTION

In recent years, the field of artificial intelligence has seen phenomenal advances in generative modelling , especially with the introduction of Generative Adversarial Networks. Since the initial paper published by Ian Goodfellow and colleagues in 2014, GANs have really transformed how machines learn to generate new data indistinguishable from reality. While most machine learning algorithms conventionally rely on discriminative models, which essentially classify inputs into classes, GANs rely on a fundamentally different adversarial training between two neural networks: one generator and one discriminator.

The generator learns to generate synthetic images from random noise, so that the synthetic images can approximate the realistic data distribution.

The discriminator will assess this generated image against real life samples and differentiate between real and fake inputs

Through this adversarial process, both networks improves iteratively, yielding the generator to produce highly realistic and good quality images

II. SYSTEM ARCHITECTURE

The system allows users to generate or reconstruct images with the use of GAN, Generative Adversarial Networks.It has mainly two components, namely Frontend: HTML/CSS/JS and Backend: Flask-Python.A text description can be provided or a 'damaged' image uploaded by the user.All user interactions occur at the backend.It consists of three modules: Text Input, Image Upload, and Output Display.The Text Input Module captures descriptive text from the user.The Image Upload Module receives damaged or incomplete image files.

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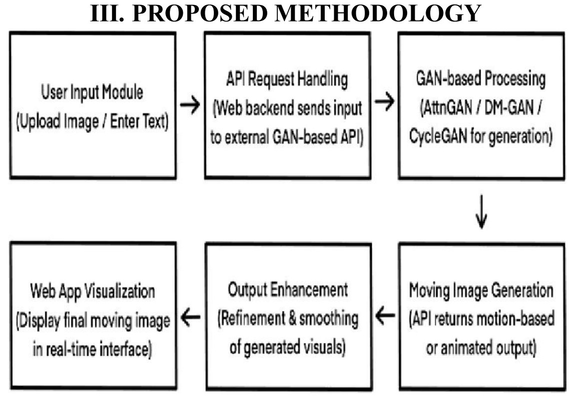
Once submitted, inputs are sent to the Backend via HTTP requests.The Request Handler in Flask receives and validates the incoming data.It cleans and formats the data for further processing.The Preprocessing Engine prepares inputs - tokenization, resizing, normalization, etc.The GAN Model Selector selects which GAN to use based on the input type.If it is text input, it goes to the Text-to-Image GAN model.If input is an image, it routes to the Image Reconstruction GAN model.

III. PROPOSED METHODOLOGY



IV. LITERATURE REVIEW

GANs have rapidly evolved from their original formulation into a divers ecosystem of architectures, training stratergies and evaluation methods targeted at high-fidelity , controllable image synthesis. This review traces the key milestones that highlighted the core technical advances ,synthesis current challenges nad describes the trends that have shaped GAN based image generation .

1. Foundational development

Adversarial learning paradigm: the original Gan framework proposed a minmax game between a generator and discriminator, establishing a flexible blueprint for learning complex data distribution s eithout explicit density estimation.

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Convolutional backbones: DCGAN standardized architectural practices, such as strided convolutions, batch norm, and ReLU/LeakyReLU, that improved training stability and image quality for natural images.

2. Architectural advances for quality and diversity:

Progressive growing: progressive GANs trained models from low to high resolutions, which helped to stabilize the synthesis for large-scale models and enabled high- resolution results.

Style-based generation: StyleGAN and StyleGAN2 introduced style modulation, stochastic variation, and architectural refinements such as demodulation and path length regularization that reached state-of-the-art photorealism and controllable attributes.

Class-conditional scaling: BigGAN relied on large-scale datasets and class conditioning, with careful regularization and training schedules, to push both the fidelity and diversity.

Attention and feature routing: Self-attention GANs enhanced global coherence by learning long-range dependencies; other later works integrated channel/spatial attention and skip connections for sharp details.

3. Conditional and cross-domain synthesis

Label and attribute conditioning: cGANs allowed controllable generation with labels, embeddings, or vectors of attributes, thus enabling targeted data synthesis and augmentation.

Image-to-image Translation: Pix2Pix paired data; CycleGAN unpaired-data-based approaches showed stylistic semantic translations of domains such as maps↔satellite and sketches↔photos using cycle- consistency and patch-based discriminators.

Text-to-image GANs: models focused on natural language conditioning, via an RNN/CNN encoder coupled with attention alignment, synthesize images from descriptions and later became enriched by contrastive pre-training that helps with semantic grounding.

4. Training strategies and regularization

Normalization and constraints: Spectral normalization bounded discriminator Lipschitz constants, while orthogonal initialization and careful weight scaling reduced exploding gradients.

Data and augmentation: ADA, DiffAug, and balanced sampling improved robustness under limited data while reducing discriminator overfitting.

Optimization schedules: Two-time-scale updates (TTUR), discriminator replay buffers, and fine-tuning of the learning rate prevented non-convergence or oscillations.

Mode-collapse mitigation: Various techniques include minibatch discrimination, diversity-sensitive losses, entropy regularization, and ensemble discriminators that would encourage wider coverage of the data manifold.

5. Evaluation metrics and benchmarks:

Distributional fidelity: Inception Score (IS) and Fréchet Inception Distance became standard for assessing realism and diversity. Kernel Inception Distance allows unbiased estimates for small samples.

Precision–recall trade-offs: Precision–recall for generative models and density–coverage diagnostics quantified overfitting vs. diversity, revealing frontier trade-offs in high-fidelity synthesis.

V. SCOPE FOR FUTURE RESEARCH

1. Photorealistic Image Synthesis

GANs generate high-resolution, realistic images of human faces, animals, and objects that are very often hardly distinguishable from real photographs.

Models like StyleGAN2 and StyleGAN3 generate faces with realistic textures, lighting, and fine details like hair strands and skin pores.

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2. Image-to-Image Translation

GANs are good for transforming one type of image into another:

Pix2Pix: This converts sketches into realistic photos, like turning the line drawing of a building into a photorealistic rendering.

CycleGAN: Translates between domains without paired data-e.g., horses ↔ zebras, summer ↔ winter landscapes.

3. Super-Resolution and Restoration

GANs enhance low-resolution images into high-resolution outputs in SRGAN.

They have been used for image inpainting-that is, filling missing regions-and deblurring, restoring corrupted or incomplete images.

4. Creative Applications

GANs generate artistic styles, paintings, and even new fashion designs.

They enable style transfer, which can apply the artistic style of one image to another.

5. Medical Imaging

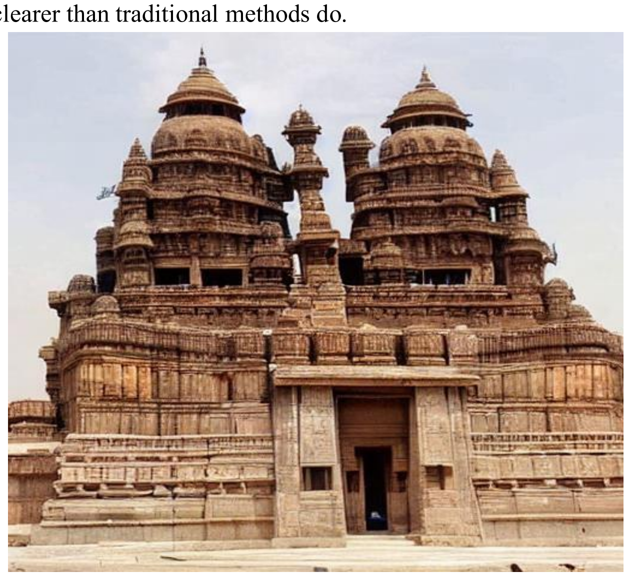
GANs generate medical scans, such as MRI and CT scans, for data augmentation that helps in building better diagnostic models. They help in denoising and enhancing clarity of medical images. 6. Challenges in Results Mode collapse: Generator produces limited variety of images. Training instability: Results depend a lot on hyperparameter tuning. Dataset bias: Images generated could generalize biases in training data, limiting diversity and fairness

RESULT:

Photorealism: GANs are able to produce highly realistic images of faces, objects, and scenes, often quite indistinguishable from real photos, using, among others, StyleGAN.

Image Translation: Models like Pix2Pix and CycleGAN convert images across the domains successfully, for example, sketches → photos, horses ↔ zebras, summer ↔ winter.

Restoration & Enhancement: GANs usually show great performance in super-resolution, inpainting, and deblurring, making images sharper and clearer than traditional methods do.



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VI. CONCLUSION

GANs have revolutionized image synthesis, making it possible for machines to create visual content that is not only realistic but also highly diverse. GANs model complex data distributions and generate outputs rivaling real-world images in quality and detail through their adversarial interaction of generator and discriminator networks. Applications involving domains such as art, entertainment, medical imaging, data augmentation, and computer vision have shown both practical utility and creative potential.

Despite these achievements, GANs still contend with long- standing issues such as training instability, mode collapse, and high computational costs that make them not very scalable and accessible. Besides, ethical concerns, especially deepfakes and misuse of synthetically generated media, raise a number of questions regarding their responsible deployment and regulation.

Looking ahead, continued research into architectural innovations, hybrid generative models, and improved evaluation metrics promises to overcome current limitations and expand the scope of GANs. With careful advancement and ethical consideration, GANs are positioned to remain a cornerstone of generative AI- driving progress in both scientific research and creative industries.

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