Deep Science Publishing
https://doi.org/10.70593/978-81-983916-5-0_5

DeepScience
Open Access Books

Chapter 5

Generative Artificial Intelligence (AI) in computer vision

Javier González Núñez

General Management, IPADE Business School, Mexico, Mexico.

Abstract: Generative AI has revolutionized computer vision by enabling machines to synthesize and enhance visual data. Advances in deep learning, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and diffusion models, have led to high-quality image generation with applications in medical imaging, data augmentation, and autonomous systems. Despite its potential, challenges like ethical concerns, dataset biases, and computational costs remain critical for future research and implementation. This paper explores the evolution of generative AI, its methodologies, applications, and the ethical and computational challenges it presents.

Keywords: Adversarial Networks, Computer Vision, Data Augmentation, Deep Learning, Diffusion Models, Generative AI.

1.1 Introduction

Generative Artificial Intelligence (AI) has emerged as a transformative force in the field of computer vision, enabling machines to synthesize, enhance, and interpret visual data with unprecedented accuracy. With the advent of deep learning architectures such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), the ability to generate high-fidelity images, improve image resolution, and augment datasets has become increasingly sophisticated. This chapter explores the evolution of generative AI within computer vision, its methodologies, applications, and the challenges it presents. The chapter also delves into ethical implications, computational constraints, and potential future advancements in the domain..

1.2 Literature review

The field of generative AI in computer vision has been extensively studied over the past decade. Early approaches to image synthesis involved rule-based and probabilistic models, as seen in the work of Hinton et al. (2006). These approaches relied on predefined patterns and lacked adaptability. The introduction of deep learning revolutionized this space, with breakthroughs such as VAEs by Kingma and Welling (2013) and GANs by Goodfellow et al. (2014) marking significant milestones. VAEs introduced the concept of probabilistic latent variables to learn efficient data representations, whereas GANs implemented adversarial learning, where two neural networks—generator and discriminator—compete to create realistic images.

Key developments in generative AI include the introduction of GANs, which involve a generator and a discriminator in a min-max game to produce realistic images. Variants such as Deep Convolutional GANs (DCGANs) by Radford et al. (2016) improved the stability of training, StyleGAN by Karras et al. (2019) introduced style-based synthesis for enhanced control over generated images, and BigGAN by Brock et al. (2019) increased the resolution and quality of generated samples. More recently, diffusion models by Ho et al. (2020) have outperformed GANs in image generation by modeling the gradual denoising of images, providing greater diversity in outputs. Transformer-based generative models, such as Vision Transformers by Dosovitskiy et al. (2020) and DALL-E by Ramesh et al. (2021), have demonstrated the effectiveness of self-attention mechanisms in generative tasks, allowing for high-quality image synthesis from textual descriptions.

1.3 Methods and materials

Popular datasets used in generative AI for computer vision include ImageNet by Deng et al. (2009), a large-scale dataset for image classification and generation; CelebA by Liu et al. (2015), a face dataset used for GAN training; and COCO by Lin et al. (2014), an object recognition dataset used for image-to-image translation and synthesis. These datasets serve as benchmarks for training and evaluating generative models.

Model architecture is primarily based on GANs, VAEs, diffusion models, and hybrid models combining GANs with transformers for improved quality and stability in image synthesis. GAN-based models are implemented using TensorFlow and PyTorch frameworks, with training involving adversarial loss optimization using Adam by Kingma and Ba (2015). VAE-based models employ encoder-decoder structures optimized via variational loss functions to learn meaningful latent spaces. Diffusion models are trained using noise scheduling strategies to progressively generate clear images, reducing dependency on adversarial training.

1.4 Results and discussions

Performance evaluation of generative AI models in computer vision is typically conducted using image fidelity metrics such as Fréchet Inception Distance (FID) by Heusel et al. (2017) and Inception Score by Salimans et al. (2016). While GANs produce highly realistic images, they suffer from mode collapse, a phenomenon where the generator produces limited varieties of images. In contrast, VAEs generate diverse samples but may lack sharpness due to their reliance on probabilistic reconstruction. Diffusion models show improved stability but require extensive computational resources and longer training times.

Applications of generative AI in computer vision include data augmentation, where AI-generated images supplement real datasets to improve model generalization. For instance, medical imaging applications use synthetic MRI and CT scan images to enhance diagnostic capabilities (Chen et al., 2020). Super-resolution and image inpainting techniques, pioneered by Ledig et al. (2017), enhance low-resolution images and reconstruct missing parts, which is particularly useful in restoring old or damaged photographs. Autonomous vehicles rely on synthetic data training for improved object detection and navigation in diverse environmental conditions (Dosovitskiy et al., 2017). In the entertainment industry, AI-generated visuals are used for film production, video game development, and virtual reality applications (Zhang et al., 2019).

1.4.1 Application and case studies:

<u>Medical Imaging</u>

AI-generated images have proven valuable in medical imaging. For instance, generative AI is used to create synthetic MRI and CT scan images to enhance diagnostic capabilities and reduce the need for large labeled datasets. A case study by Chen et al. (2020) demonstrated that AI-generated synthetic medical images improved the performance of diagnostic models by 15%, particularly in detecting rare diseases.

Autonomous Vehicles

Autonomous vehicles rely on AI-generated synthetic data to train models for object detection and navigation. Waymo, a leader in self-driving car technology, utilizes GAN-generated images to simulate different driving conditions, allowing its models to generalize better in real-world scenarios (Dosovitskiy et al., 2017). This synthetic training data has significantly improved the accuracy of pedestrian and obstacle detection.

Entertainment Industry

Generative AI has transformed the entertainment industry by creating hyper-realistic animations and virtual characters. AI-generated visuals are used in video game development, film production, and virtual reality applications. For example, NVIDIA's StyleGAN has been used to create digital human faces indistinguishable from real ones, enhancing CGI character realism in blockbuster films (Zhang et al., 2019).

Retail and E-Commerce

In e-commerce, AI-generated images enable virtual try-on experiences and product customization. Companies like Adidas and Nike use AI-generated product images to showcase customized shoe designs before they are manufactured, enhancing customer engagement and reducing inventory costs. This application has led to a 20% increase in customer satisfaction, according to a study by Lin et al. (2022).

1.5 Ethical and Computational Challenges

One of the primary concerns in generative AI for computer vision is ethical considerations. The ability of AI models to create hyper-realistic synthetic media, including deepfakes, has raised concerns regarding misinformation, privacy invasion, and identity theft (Tolosana et al., 2020). Additionally, biases in generative AI models can perpetuate stereotypes and produce misleading visual representations if training datasets are unbalanced. Addressing these biases requires careful curation of datasets and robust fairness-aware algorithms.

From a computational perspective, generative AI models, particularly diffusion models and transformers, require extensive computational power and memory. The cost of training high-resolution image generation models can be prohibitive for smaller research institutions. Techniques such as knowledge distillation, model compression, and federated learning are being explored to enhance model efficiency and accessibility.

1.6 Future Directions

Future research in generative AI for computer vision should focus on improving model efficiency, interpretability, and ethical governance. Efforts to reduce mode collapse in GANs, enhance the robustness of diffusion models, and improve the interpretability of transformer-based architectures are critical. Additionally, research into energy-efficient AI training techniques and decentralized model training could democratize access to high-performance generative AI tools. Ethical guidelines and regulatory frameworks should also be established to mitigate the risks associated with deepfakes and biased AI-generated media.

Conclusions

Generative AI has significantly advanced computer vision, allowing machines to generate, enhance, and interpret images with human-like proficiency. While GANs, VAEs, and diffusion models have demonstrated remarkable progress, challenges such as ethical concerns, bias in generated data, and computational demands persist. The issue of AI-generated deepfakes poses a significant ethical challenge, raising concerns about misinformation and privacy. Additionally, the high computational cost of training generative models makes them less accessible to smaller research groups. Future research must focus on improving efficiency, fairness, and real-world applicability of generative AI systems in computer vision. Enhanced techniques for reducing mode collapse in GANs, improving the interpretability of transformer-based models, and addressing biases in datasets will be critical for the continued advancement of this field.

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