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Generative AI: Exploring Models, Mechanisms, and Emerging Applications

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Abstract:

Generative Artificial Intelligence has emerged as a transformative branch of machine learning capable of producing original text, images, audio, and code. This paper reviews the core architectures underlying generative models — including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Transformers, and Diffusion models and examines their working principles, realworld applications, and associated challenges.

Beyond a structural review, this work presents a comparative evaluation of the four architectures across training stability, sample fidelity, and computational cost, and discusses the societal, ethical, and computational implications of large-scale generative systems. The objective is to provide a structured, evidence-based foundation for researchers and practitioners engaging with this rapidly evolving field.

Keywords: Generative AI, GANs, Transformers, Diffusion Models, Large Language Models, Explainable AI.

1. Introduction

Generative AI is a rapidly growing branch of artificial intelligence that focuses on generating new content such as text, images, sound, video, and computer programs. Unlike traditional AI systems that analyze existing data or make predictions, generative AI models learn patterns from large data sets and use those patterns to produce original, human-like outputs. Technologies such as large language models (LLMs), generative adversarial networks (GANs) and diffusion models have significantly improved the capabilities of generative artificial intelligence.

The mechanisms behind generative artificial intelligence include techniques such as implicit learning, neural networks, transforms, attention mechanisms, and probabilistic generation. These technologies enable artificial intelligence systems to

understand complex patterns, generate meaningful responses, and adapt their outputs to user instructions. Recent advances have made artificial intelligence more accessible to develop in fields such as education, healthcare, business, entertainment, software development, and scientific research.

The growing applications of artificial intelligence for development demonstrate its potential to transform the way people work, learn, communicate and create. Content creation, personalized education, drug discovery, virtual assistants, automated programming, creative design and synthetic data generation are some of the rapidly expanding applications of artificial intelligence. At the same time, issues of misinformation, bias, privacy, copyright, security, and ethical use must be carefully considered. Therefore, to effectively and responsibly use this transformative technology, it is essential to understand the models, mechanisms and emerging applications of generative artificial intelligence.

Artificial Intelligence has traditionally focused on recognition and prediction — classifying images, forecasting outcomes, and detecting patterns in existing data. Generative AI shifts this paradigm toward creation, producing new, original content that did not exist in the training data itself.

1.1 From Analysis to Synthesis

Traditional AI systems classify and predict based on observed inputs. Generative AI models, by contrast, learn the underlying distribution of a dataset and sample novel outputs from it — turning a passive, analytical capability into an active, creative one.

1.2 Data-Driven Creativity

Generative models learn statistical patterns from massive datasets in order to synthesize realistic content. The quality, diversity, and coherence of generated output is directly tied to the scale and richness of the training corpus.

1.3 Rapid Mainstream Adoption

Tools such as ChatGPT and Stable Diffusion have brought generative AI from research labs into everyday use, making it accessible to non-technical users for writing, design, coding, and beyond.

Example — Everyday adoption: A marketing team uses ChatGPT to draft ad copy in minutes and Stable Diffusion to generate accompanying product imagery, tasks that previously required a copywriter and a graphic designer.

Generative AI now underpins innovation across content creation, software engineering, scientific research, and education, making it one of the most consequential technologies discussed in current AI/ML research. This paper

structures its discussion around model foundations, comparative evaluation, applications, and open challenges.

2. Literature Review

The field's foundations were laid across a short but intense period of innovation between 2013 and 2022, with each milestone architecture unlocking new categories of generative capability.

- 2013–2014 — Variational Autoencoders: Kingma and Welling proposed a probabilistic approach to learning latent representations, enabling smooth, continuous generation via an encoder–decoder framework.
- 2014 — Generative Adversarial Networks: Goodfellow et al. introduced the adversarial training framework, pitting a generator against a discriminator to progressively improve realism.
- 2017 — The Transformer Architecture: Vaswani et al. introduced self-attention, laying the foundation for modern large language models (LLMs).
- 2020–2022 — Diffusion and LargeScale Models: Denoising diffusion models and large language models achieved state-of-the-art generation quality across image and text domains.

3. Core Generative Model Architectures

Generative AI technology relies on various model architectures designed to learn patterns from existing data and generate new and natural content. The most prominent of these architectures include Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Transformer-based models, and Diffusion Models.

3.1 Generative Adversarial Networks (GANs)

GANs consist of a generator and a discriminator network that compete against each other. The generator tries to produce increasingly realistic samples, while the discriminator learns to distinguish real data from generated data, driving both networks to improve in tandem.

Example — GANs: StyleGAN, used to generate photorealistic human faces of people who do not exist (e.g., thispersondoesnotexist.com), and CycleGAN, used for image-to-image translation such as converting horse photos into zebra photos.

3.2 Variational Autoencoders (VAEs)

VAEs encode data into a probabilistic latent space and then decode samples from that space to generate variations. Because the latent space is continuous and structured, it enables smooth interpolation between generated outputs.

Example — VAEs: Anomaly detection in industrial sensor data, where a VAE trained on normal operating conditions flags inputs that reconstruct poorly as potential faults; also used in drug-molecule generation by interpolating within a learned chemical latent space.

3.3 Transformers

Transformers use self-attention mechanisms to model long-range dependencies between elements of a sequence, allowing every token to be weighed against every other token in parallel. This architecture underlies virtually all modern large language models.

Example — Transformers: GPTfamily models generating human-like text for chatbots and coding assistants, and BERT-style models used for search-query understanding and document classification.

3.4 Diffusion Models

Diffusion models iteratively denoise random noise into coherent, highfidelity outputs. A neural network is trained to reverse a gradual noising process, refining pure noise into a realistic sample over many steps.

Example — Diffusion Models: Stable Diffusion and DALL·E 3 generating photorealistic or artistic images from text prompts, and diffusion-based tools used for video generation and 3D asset synthesis.

4. Working of Generative AI Architecture Models:

4.1. GAN — Adversarial Training

A Generative Adversarial Network (GAN) consists of two main neural networks: the Generator (G) and the Discriminator (D). These networks work together through an adversarial learning process. The generator creates synthetic data, while the discriminator evaluates whether the data is real or generated. The interaction between these two components enables GANs to produce increasingly realistic outputs.

4.1.1. Generator

The Generator is responsible for producing new synthetic samples. It takes a random noise vector from a latent space as input and transforms it through a series of neural network layers to generate an output.

For image generation, the generator may use layers such as fully connected layers, convolutional layers, upsampling layers, and activation functions. Its objective is to generate samples that are sufficiently realistic to be classified as real by the discriminator.

Input: Random noise vector

Processing: Neural network transformation **Output:** Synthetic data sample

4.1.2. Discriminator

The Discriminator is a binary classification network that receives both real samples from the dataset and synthetic

samples generated by the generator. It predicts the probability that an input sample is real.

For image-based GANs, the discriminator commonly uses convolutional layers to extract important features from images, followed by fully connected layers that produce the final classification.

Input: Real or generated sample

Processing: Feature extraction and classification

Output: Probability of being real

4.1.3. Interaction Between Generator and Discriminator

The two networks are connected through an adversarial training process. The generator attempts to fool the discriminator, while the discriminator attempts to correctly identify generated samples.

The basic architecture can be represented as:

Random Noise → Generator → Generated Sample → Discriminator → Real/Fake Prediction

At the same time:

Real Data → Discriminator → Real/Fake Prediction

The generator receives feedback from the discriminator and updates its parameters to produce more realistic samples. The discriminator also updates its parameters to improve its ability to distinguish real data from generated data.

4.1.4. GAN Architecture Flow

The overall architecture follows these steps:

1. A random noise vector is selected from the latent space.
2. The noise vector is provided as input to the generator.
3. The generator transforms the noise into a synthetic sample.
4. The synthetic sample is passed to the discriminator.
5. Real training data is also provided to the discriminator.
6. The discriminator predicts whether each sample is real or fake.
7. The prediction error is used to update both networks during training.

4.1.5. Architectural Variations

Different GAN architectures have been developed for specific applications. Deep Convolutional GANs (DCGANs) use convolutional networks for image generation. Conditional GANs (cGANs) generate outputs based on additional information such as class labels or text descriptions. CycleGAN is designed for image-to-image translation without requiring paired training data. These variations extend the basic GAN architecture to support more complex generation tasks.

The GAN architecture is based on the interaction of a generator and a discriminator. The generator learns to create realistic synthetic data, while the

discriminator learns to distinguish generated data from real data. Through repeated adversarial training, both networks improve their performance, making GANs an important architecture for generative AI applications.

4.2. VAE — Encode–Decode

A Variational Autoencoder (VAE) is a generative deep-learning model that learns a compact probabilistic representation of input data and uses this representation to generate new data. Its working principle is based on two main components: the Encoder and the Decoder.

4.2.1. Encoder

The encoder receives the input data and transforms it into a lower-dimensional latent representation. Unlike a traditional autoencoder, a VAE does not directly produce a single latent vector. Instead, it learns the parameters of a probability distribution, usually the mean (μ) and variance (σ^2).

The encoder can be represented as:

Input → Encoder → Mean (μ) and Variance (σ^2)

These parameters describe the probability distribution from which a latent variable is sampled.

4.2.2. Latent Space and Reparameterization

The latent representation is obtained by sampling from the distribution learned by the encoder. To allow gradientbased training, VAEs use the reparameterization trick:

$$z = \mu + \sigma \odot \varepsilon$$

where z is the latent vector, μ is the mean, σ is the standard deviation, and ε is random noise sampled from a standard normal distribution.

This process allows the model to learn a smooth and meaningful latent space.

4.2.3. Decoder

The sampled latent vector z is then passed to the decoder. The decoder transforms the latent representation back into the original data space and generates a reconstructed sample.

The process can be represented as:

Latent Vector (z) → Decoder → Reconstructed Output

During training, the decoder learns to generate an output that is as similar as possible to the original input.

4.4.4. Training Objective A VAE is trained using two main loss components:

- Reconstruction Loss: Measures how closely the reconstructed output matches the original input.
- KL Divergence Loss: Encourages the learned latent distribution to remain close to a standard normal distribution.

The overall VAE loss can be expressed as:

VAE Loss = Reconstruction Loss + KL Divergence Loss

This combination enables the VAE to both reconstruct existing data and generate new samples.

4.4.5. Overall Working Process

The complete encode–decode process is:

Input Data → Encoder → Latent Distribution → Sampling → Latent Vector → Decoder → Reconstructed Data Once training is complete, new random vectors can be sampled from the latent space and provided to the decoder to generate new data samples.

The encode–decode mechanism is the fundamental working principle of a VAE. The encoder converts input data into a probabilistic latent representation, while the decoder converts the latent representation back into the data domain. By learning a structured latent space,

VAEs can perform both data reconstruction and new data generation, making them an important architecture in generative AI. **4.3. Transformer**

Transformer — Self-Attention

A Transformer is a deep-learning architecture widely used in modern Generative AI for processing and generating sequential data such as text, code, audio, and other structured information. The key mechanism of a Transformer is self-attention, which enables the model to identify relationships between different elements of an input sequence.

4.3.1. Input Tokenization

The Transformer first divides the input into smaller units called tokens. For example, a sentence is converted into a sequence of words, subwords, or other token units. Each token is then converted into a numerical vector called an embedding.

Input Text → Tokenization → Token Embeddings Since Transformers process tokens in parallel, positional information is added to the embeddings so that the model can understand the order of the tokens.

4.3.2. Self-Attention Mechanism

Self-attention allows each token to examine other tokens in the sequence and determine which ones are important for understanding its meaning. For example, in the sentence:

"The student submitted the assignment because it was completed."

The model can use attention to determine what the word "it" refers to by examining the relationships between the words in the sentence.

4.3.3. Query, Key, and Value

Self-attention uses three representations:

- Query (Q): Represents what information a token is looking for.
- Key (K): Represents the information associated with each token.

- Value (V): Contains the actual information that can be passed to the output.

The attention calculation is commonly expressed as:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T / \sqrt{d_k})V$$

where d_k represents the dimension of the key vectors.

Query and Key vectors determine how strongly tokens should attend to one another. The resulting attention weights are then applied to the Value vectors.

4.3.4. Multi-Head Attention

Transformers commonly use MultiHead Attention, in which several selfattention operations are performed simultaneously. Each attention head can learn different relationships within the input.

For example, one head may focus on grammatical relationships, while another may focus on semantic relationships. The outputs from the different heads are combined to produce a richer representation.

4.3.5. Feed-Forward Network

After the attention operation, the resulting representation is passed through a feed-forward neural network. This network further processes the information and learns complex patterns. A Transformer layer generally includes:

Self-Attention → Add & Normalize → Feed-Forward Network → Add & Normalize

Residual connections and normalization help improve training stability and information flow through the network.

4.3.6. Autoregressive Generation In generative Transformer models, such as decoder-based language models, tokens are generated one at a time. The model uses previously generated tokens as context to predict the next token.

For example:

The → The student → The student is → The student is learning → ...

At each step, the model calculates probabilities for possible next tokens and selects one according to its generation strategy.

4.3.7. Overall Working Process The working principle of a Transformer can be summarized as:

Input → Tokenization → Embedding + Position Information → Self-Attention → Multi-Head Attention → Feed-Forward Network → Output **For text generation:**

Input Context → Transformer Layers → Next-Token Prediction → Generated Token → Updated Context → Next-Token Prediction

The self-attention mechanism is the core principle that enables Transformers to understand relationships between different parts of an input sequence. By using Query,

Key, and Value representations, the model determines which tokens are important to one another. Combined with multi-head attention, feed-forward networks, positional information, and autoregressive generation, this architecture forms the foundation of many modern Large Language Models (LLMs) and other generative AI systems.

4.4. Diffusion — Iterative Denoising

Diffusion Models are an important class of generative AI models that can generate high-quality images, audio, video, and other forms of data. Their fundamental working principle is iterative denoising, in which the model learns to gradually remove noise from a randomly generated noisy sample until a meaningful output is obtained.

4.4.1. Forward Diffusion Process

During training, the model gradually adds random noise to an original data sample over a series of steps. Initially, the data contains little or no noise. As the process continues, increasing amounts of noise are added until the original structure is almost completely destroyed.

Original Data → Slight Noise → More Noise → Almost Pure Noise

The purpose of this process is to teach the model how data changes when noise is progressively introduced. **4.4.2. Learning the Denoising Process**

The model is trained to predict and remove the noise added at each step. It learns the relationship between a noisy sample and the original data distribution.

For a noisy sample at timestep t, the model estimates the noise present in that sample. The model then uses this prediction to determine how the noise should be reduced.

4.4.3. Reverse Diffusion Process

During generation, the process is reversed. The model starts with random noise and repeatedly removes a small amount of noise at each step.

Random Noise → Denoising Step 1 → Denoising Step 2 → ... → Final Generated Data

This iterative process gradually reveals meaningful structures and produces the final generated output.

4.4.4. Iterative Denoising

The key feature of diffusion models is that generation does not usually occur in a single step. Instead, the model performs multiple denoising iterations. At each iteration:

1. The current noisy sample is provided to the model.
2. The model predicts the noise present in the sample.
3. The predicted noise is removed partially.
4. The resulting sample becomes slightly clearer.
5. The process is repeated for subsequent timesteps. Through

these repeated steps, random noise is transformed into a coherent and realistic output.

4.4.5. Conditional Generation

Diffusion models can also generate content based on additional conditions. For example, in text-to-image generation, a text prompt provides information that guides the denoising process toward an image matching the description.

The general process is:

Text Prompt → Conditioning Information → Iterative Denoising → Generated Image

This allows users to control the type, content, and characteristics of the generated output. **4.4.6. Overall Working Process**

The complete principle can be summarized as:

Training:

Real Data → Gradual Noise Addition → Noisy Data → Learn Noise Removal

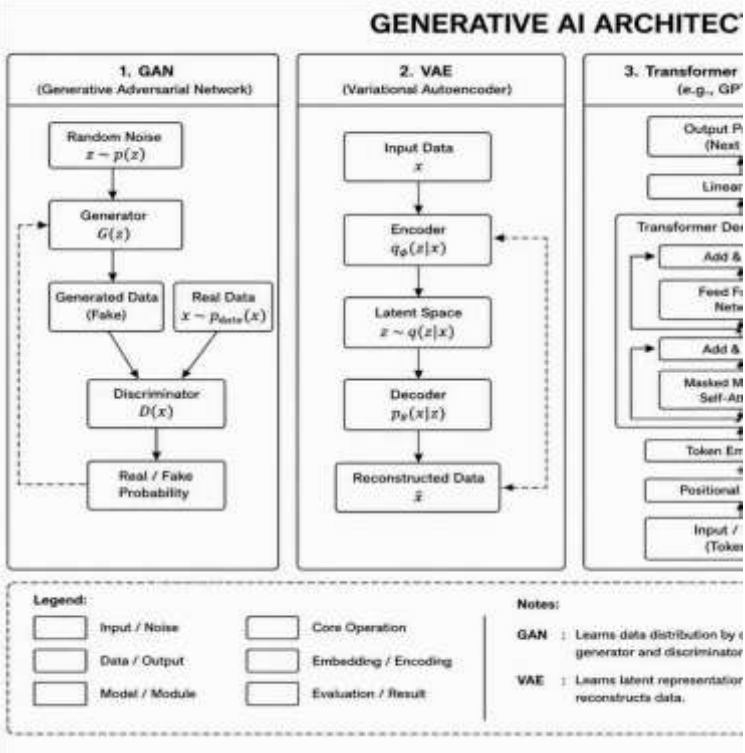
Generation:

Random Noise → Iterative Noise Prediction and Removal → Clean Generated Data

5. Applications

Diffusion models are widely used for:

- Text-to-image generation
- Image editing and restoration
- Image super-resolution
- Video generation
- Audio and music generation
- 3D content generation



- Scientific and molecular data generation

The iterative denoising mechanism is the fundamental working principle of diffusion models. During training, the model learns how noise is added to data and, more importantly, how that noise can be removed. During generation, it starts with random noise and progressively denoises it

Architecture	Sample Fidelity	Training Stability	Inference Speed
GAN	High (sharp)	Low	Fast
VAE	Moderate	High	Fast
Transformer	High (text)	High	Moderate
Diffusion	Very High	High	Slow

over multiple steps to produce meaningful and realistic content. This approach has made diffusion models one of the most powerful architectures in modern generative AI.

6. Comparative Evaluation of Architectures

Table 1 summarizes the four architectures across sample fidelity, training stability, inference speed, computational cost, and their best-fit use cases.

Table 1. Comparative evaluation of generative model architectures.

7.General Generative Pipeline

Regardless of architecture, most generative systems follow a common five-stage pipeline, summarized in Table 2.

Table 2. General generative AI pipeline.

Stage	Name	Description
01	Data Collection	• Large-scale text, image, or audio corpora are gathered and • Transformer-based foundation pre-processed. models
02	Representation Learning	A neural network learns latent patterns and structure Expanding cloud infrastructure • within the data. • New industry-specific use cases
03	Model Training	Parameters are optimized using adversarial, variational, or **9. Applications and Impact of** diffusion objectives.**Generative AI:**
04	Sampling & Generation	New content is generated by sampling and decoding from Generative AI has evolved from a the learned researchspace. -oriented technology into a
05	Evaluation & Refinement	practical tool with applications across Outputs are assessed for quality, bias, and alignment, then numerous fields. By generating text, fine-tuned. images, audio, video, code, and synthetic

8. Generative AI Market Growth Outlook

The global generative AI market is projected to expand rapidly through the early 2030s, driven by enterprise adoption, foundation-model innovation, and expanding industry use cases (Table 3).

Table 3. Global generative AI market size (USD Billion).

Year (Index)	Global Market Size
Year 3 (projected)	USD 324.7 Billion

Key Drivers: data, generative AI is changing how individuals and organizations create, analyze, and interact with information. Its impact can be observed in areas such as education, healthcare,

business, software development, media, and scientific research.

9.1. Content & Media

Generative AI enables the creation and modification of images, music, video, animation, and written content. Designers, authorship, deepfakes, and the authenticity of digital content have increased. Automated generation of text, images, video, and music for creative industries.

Example

: A film studio uses generative video tools for pre-visualization storyboards, and musicians use AI composition tools (e.g., Suno) to prototype melodies.

9.2. Software Engineering

Generative AI has significantly influenced software development through code generation, debugging, documentation, testing, and code explanation. AI coding assistants can help developers write programs more quickly and explore alternative implementations. Nevertheless, generated code requires human review because it may contain errors, security vulnerabilities, or inefficient solutions. Code generation, debugging assistance, and automated documentation.

Example — Software Engineering: Developers use Claude Code or GitHub Copilot to generate boilerplate functions, catch bugs during review, autogenerate docstrings for a legacy codebase.

Year (Index)	Global Market Size	Notes artists, filmmakers, and ators
Year 1	USD 22.2 Billion	se technologies for prototyping enterprise adoption and perimentation. At the same
Year 2	USD 29.6 Billion time, co	cerns Foundationrelat-ed mode o copyright,

9.3. Healthcare

In healthcare, generative AI is being explored for applications such as medical documentation, clinical decision support, drug discovery, medical image analysis, and synthetic data generation. It can help reduce repetitive administrative work and accelerate research processes. Since healthcare applications involve sensitive information and high-stakes decisions, accuracy, privacy, validation, and human oversight are essential. Synthetic medical data, drug discovery support, and diagnostic assistance.

Example: Generative models create synthetic patient records to train diagnostic classifiers without exposing real patient data, and diffusion-based models assist in generating candidate protein structures for drug discovery.

9.4. Education

Generative AI can support personalized learning by generating

explanations, summaries, practice questions, study materials, and interactive learning content. AI-based systems can adapt explanations to different levels of understanding and assist educators in preparing instructional materials. However, responsible use is important to prevent overdependence and maintain academic integrity. Personalized tutoring content and adaptive assessment generation.

Example: An LLM-based tutor generates practice problems calibrated to a student's current skill level and explains mistakes in natural language.

9.5. Business Operations

Organizations use generative AI for content creation, customer support, report generation, marketing, data analysis, and knowledge management. AI-powered assistants can automate routine tasks and help employees access information more efficiently. This can improve productivity while allowing human workers to focus on more complex and creative activities. Automated reporting, chatbots, and design prototyping.

Example: A retail company deploys an LLM-powered customer service chatbot that resolves routine order queries, reducing average response time from hours to seconds.

9.6. Scientific Research

Generative AI is increasingly being investigated as a tool for scientific discovery. It can assist with molecular design, material discovery, simulation, synthetic data generation, and research summarization. By generating and evaluating possible solutions, AI can help researchers explore large problem spaces more efficiently. Simulation and synthetic datasets accelerating discovery.

Example: DeepMind's generaive approaches to protein structure prediction (AlphaFold-adjacent work) illustrate how generative modeling accelerates biological discovery.

The impact of generative AI can be considered in terms of productivity, creativity, accessibility, and automation. It can reduce the time required for many content-generation tasks and provide individuals with tools that were previously available mainly to specialists. However, its benefits are accompanied by challenges such as hallucinations, bias, misinformation, privacy risks, copyright concerns, job displacement, and security threats.

Generative AI is having a broad impact across both technical and nontechnical domains. Its ability to generate and transform information has created new opportunities for automation, creativity, research, and personalized services. At the same time, effective adoption requires attention to reliability, ethics, privacy, security, and human oversight. Therefore, the long-term impact of generative AI will

depend not only on technological advancement but also on its responsible and appropriate use.

10. Opportunities and Emerging Challenges:

Generative AI presents significant opportunities for innovation across various domains while also introducing new technical, ethical, social, and security challenges. Its rapid development has created opportunities to improve productivity, creativity, automation, personalization, and scientific discovery. At the same time, responsible adoption requires careful consideration of the limitations and risks associated with these technologies.

10.1. Opportunities

- Accelerated content and product development
- Scalable personalization across domains
- New research tools via synthetic data
- Lowered barriers to creative and technical work

10.2. Open Challenges

- Bias, fairness, and misinformation risks
- Intellectual property and copyright ambiguity
- High computational and energy costs
- Need for explainability, safety, and governance

Example — Open challenge in practice: A generative image model trained predominantly on Western media produces stereotyped or unrepresentative outputs when prompted for imagery from underrepresented cultures, illustrating the fairness challenge in deployment.

11. Conclusion

Generative AI represents a foundational shift from analytical to creative machine intelligence. As GANs, VAEs, Transformers, and Diffusion models mature, their responsible deployment will depend on transparency, efficiency, and governance.

- Multimodal generative systems, combining text, image, audio, and video generation within a single model.
- Agentic and autonomous AI workflows, where generative models plan and execute multi-step tasks.
- Explainable and sustainable model design, balancing capability with interpretability and energy efficiency.

Generative Artificial Intelligence has emerged as a transformative technology capable of creating new content, including text, images, audio, video, and computer code. This study examined the fundamental models, mechanisms, architectures, applications, and emerging challenges associated with Generative AI.

Overall, Generative AI represents a major advancement in artificial intelligence. Its continued development has the potential to transform numerous industries, but achieving sustainable benefits requires responsible design, appropriate regulation, human oversight, and careful consideration of ethical and societal impacts.

12. Future Scope

The future of Generative AI is expected to focus on improving the accuracy, efficiency, reliability, controllability, and safety of AI models. Future research may explore more efficient architectures that require fewer computational resources while maintaining high-quality performance.

The development of multimodal AI systems is another important direction. Future models are expected to integrate text, images, audio, video, and other forms of information more effectively, enabling more natural and intelligent human–AI interaction.

Research into explainable and trustworthy AI will also become increasingly important. Improved transparency can help users understand how AI systems produce their outputs and identify potential errors or biases.

Future Generative AI systems may also provide stronger personalization and domain-specific capabilities, allowing models to be adapted for fields such as medicine, education, engineering, finance, and scientific research. Privacy-preserving methods and secure AI architectures will be essential when working with sensitive information.

Another important area is AIassisted scientific discovery, where generative models can contribute to drug development, material design, simulation, and automated experimentation. HumanAI collaboration is also expected to become more advanced, with AI supporting rather than completely replacing human decision-making and creativity.

In conclusion, the future scope of Generative AI is broad and promising. Continued research should focus not only on making models more powerful but also on making them reliable, transparent, secure, efficient, ethical, and beneficial to society.

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