International Journal of Research in Advent Technology, Vol.12, No.4, December 2024
E-ISSN: 2321-9637
Available online at www.ijrat.org

Generative AI: A Structured Review, Techniques, Application and Future Prospects

Anagha Abhijit Jawalkar, Suwarna Gothane, Alessandro Bruno

Abstract—Generative AI (GAI) is a rapidly growing field with a wide range of applications. In recent years, the study of artificial intelligence (AI) has undergone a paradigm shift. This has been fuelled by the revolutionary potential of generative models in both supervised and unsupervised learning settings. Generative AI has shown state-of-the-art performance in handling challenging real-world issues in fields including image translation, medical diagnostics, textual imagery fusion, natural language processing, and more. This paper offers an extensive assessment and analysis of recent advancements and approaches in generative artificial intelligence, along with a detailed description of their applications, including models tailored to particular applications and future directions. The study also highlights how important it is to address privacy and data security concerns in GAI and responsible use.

Keywords - Artificial intelligence, Generative artificial intelligence, Systemic review, Large Language Models, Multimodal AI integration

I. Introduction

The introduction of generative artificial intelligence, often known as generative AI or Genai, has been largely responsible for the recent advances in AI. "Generative AI" refers to artificial intelligence systems that use generative models to produce text, images, and/or other types of media. Through the process of learning the underlying patterns and structures in their training data, these models generate new data that exhibits comparable features. This systematic review's goal is to compile, assess, and synthesize the body of knowledge regarding Genai. A rigorous review of important application approaches and their difficulties is presented in this study.

II. Techniques

Numerous cutting-edge methods from machine learning, deep learning, and other computational domains are used in generative AI. These methods are intended to produce new data like text, pictures, music, or even.

The main methods employed in generative AI are listed below.

A. Generative Adversarial Networks (GANs)

A state-of-the-art method for generative modeling in deep learning, GANs frequently make use of topologies such as convolutional neural networks. For the model to generate new instances that remotely resemble the original dataset, generative modeling aims to automatically detect patterns in incoming data. One potent family of neural networks used for unsupervised learning is called Generative Adversarial Networks. A discriminator and a generator are the two neural networks that make up a GAN. To create synthetic data that is exact replicas of real data, they employ adversarial training[4]

The discriminator's job is to determine if the generated image is real or not, whereas the generator's primary function is to continuously produce phony data using noise[14]. The discriminator's only function is to determine whether or not the output generated by the generator is phony. It is trained using actual images of the domain that the generator is attempting to create artificially. The entire system is based on the dynamics of a zero-sum game, where the winner stays the same and the loser model must constantly adjust its parameters until the discriminator can no longer determine whether the generator output is phony or not [2].

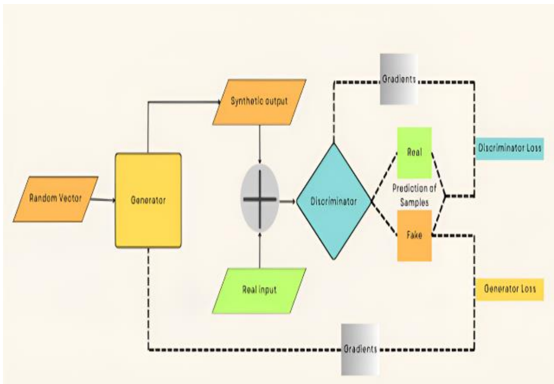

Figure 1: GAN network

Figure 1 shows how the discriminator and generator cooperate. By supplying the artificially created image with the goal that it be validated as authentic, the generator seeks to fool the discriminator. The output signal is produced by the discriminator, which separates real images from fake ones. After that, this output signal is sent to the discriminator and

Manuscript revised on December 10, 2024 and published on December 17, 2024
Mrs. Anagha Abhijit Jawalkar, *Assistant Professor, Dept of Artificial Intelligence & Data Science, D. Y. Patil College of Engineering Akurdi, Pune, India. anagha.jawalkar@gmail.com*
Dr. Suwarna Gothane, *Associate Professor, Dept of Artificial Intelligence & Data Science, D. Y. Patil College of Engineering Akurdi, Pune, India. gothane.suvarna@gmail.com.*
Dr. Alessandro Bruno, IULM University, Milan, Italy

doi: 10.32622/ijrat.124202408

generator, enabling the generator to provide higher-quality synthetic output[15] Additionally, the discriminator uses the signal to adjust its weights to provide more accurate predictions if it is unable to demonstrate that the image is fraudulent. It is crucial to remember that in this entire architecture, the generator only learns from the output signal of the discriminator, which has access to the real image, synthetic image, and its signal output[8]

Applications: Image generation (e.g. DeepFake), style transfer, and synthetic data creation.

B. Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs), first presented by Kingma et al. [7], are another model in the realm of generative AI. It belongs to the families of variational Bayesian techniques and probabilistic graphical models. An encoder and a decoder make up the VAEs. A decoder reverts the encoder's latent output to the original input shape after the encoder has encoded the input in a lower dimension known as latent space. Throughout the entire procedure, the usual Gaussian distribution is used to introduce variation into the latent space. After the variance is introduced, the primary objective is to produce an output with a mean and variance comparable to the input. This offers an organized method for learning significant representations of data and then generating new samples from that data distribution.

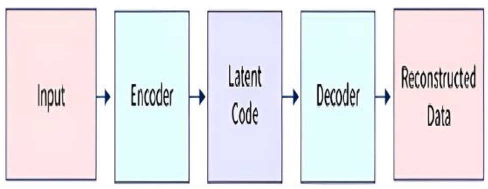

Figure 2: working of Variational encoder

Applications: Image and text generation, anomaly detection, and drug discovery.

C. Transformers

Vaswani et al. [17] presented more generative AI methods known as Transformers. This innovative architecture continues to impact later neural network designs and set the groundwork for several applications, such as language production and machine translation. By highlighting the importance of attention mechanisms in sequence-to-sequence tasks, the paper advanced the state of the art. Transformers learn the many relationships and patterns between the input by using both self-attention and multi-head attention mechanisms. This allows them to understand the dependencies between items regardless of their distance from one another. These techniques are frequently used in Natural Language Processing in conjunction with positional encoding, which is appended to the input sequence to enable the transformers to track the location of a particular word within the input sequence[12]

Applications: Language modeling, text-to-image generation, and summarization.

D. Diffusion Models

Salimans et al. [11] proposed the Diffusion Models approach, which was created to enhance the Simple Generative Adversarial Network's performance. Later, as a foundation for generative models, Kingma et al. [5] presented Inverse Autoregressive Flow (IAF), a variation of the diffusion model. One kind of normalizing low is IAF. This kind of generative model uses a sequence of invertible transformations to convert a basic base distribution into the target distribution to learn complex probability distributions.

Applications: High-quality image synthesis, video generation, and 3D modeling.

E. Reinforcement Learning with Human Feedback (RLHF)

Reinforcement learning from human feedback (RLHF) is a machine learning technique that uses direct human feedback to develop a "reward model" before using reinforcement learning to maximize an AI agent's performance.

Reinforcement learning from human preferences (RLHF) is particularly well-suited for tasks with complex, ill-defined, or challenging-to-specify goals. For instance, defining "funny" mathematically would be problematic (or even impossible) for an algorithmic solution, whereas rating jokes produced by a large language model (LLM) is simple for humans. By distilling that human input into a reward function, the LLM's joke-writing skills may then be enhanced. Along with other methods like supervised and unsupervised learning, RLHF is a particular methodology used to teach AI systems to look more human. The model's reactions are first contrasted with human responses. After that, a human evaluates the caliber of various machine responses, assigning a score that Reactions sound more genuine. Inherently human traits like friendliness, the appropriate level of contextualization, and mood can all be used to determine the score. This method fine-tunes models by combining user feedback with reinforcement learning. In conversational AI, it is frequently used to match model outputs to user preferences.

Techniques for RLHF improve user satisfaction and AI performance while introducing intricate training parameters. Four steps of RLHF are completed before the model functions well. An internal company knowledge base chatbot that employs RLHF for refining is used as an example of a language model in this context. Only a summary of the RLHF learning process is provided. The model training and policy refining for RLHF are highly mathematically difficult. On the other hand, RLHF's intricate procedures are clearly described and frequently feature pre-built algorithms that only require your particular inputs.

1. Data collection

Before performing ML tasks with the language model, a set of human-generated prompts and responses are created for

doi: 10.32622/ijrat.124202408

the training data. This set is used later in the model's training process[6]

2. Supervised fine-tuning of a language model

A commercial pre-trained model can be used as the RLHF base model. You can use methods like retrieval-augmented generation (RAG) to adjust the model to the internal knowledge base of the business. You compare the model's answer to the preset prompts with the human responses gathered in the preceding stage once it has been fine-tuned.
The degree of similarity between the two can be determined mathematically.
The machine-generated responses, for instance, can be given a score ranging from 0 to 1, where 0 represents the least accuracy and 1 represents the highest. The model now has a policy that is intended to generate replies that are more similar to human responses based on these scores. This policy serves as the foundation for all upcoming model decisions.

3. Building a separate reward model

The core of RLHF is training a separate AI *reward model* based on human feedback, and then using this model as a reward function to optimize policy through RL. Given a set of multiple responses from the model answering the same prompt, humans can indicate their preference regarding the quality of each response. You use these response-rating preferences to build the reward model that automatically estimates how high a human would score any given prompt response.

4. Optimize the language model with the reward-based model

The language model then uses the reward model to automatically refine its policy before responding to prompts. Using the reward model, the language model internally evaluates a series of responses and then chooses the response that is most likely to result in the greatest reward. This means that it meets human preferences in a more optimized manner.

The following image shows an overview of the RLHF learning process -

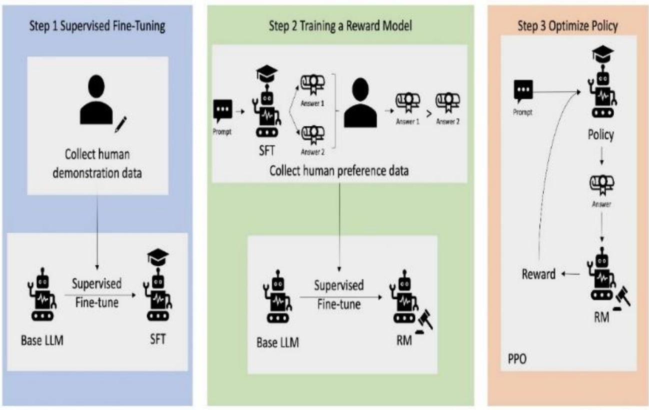

Figure 3: RLHF Learning Process

Applications: Chatbots, customer service agents, and personalized recommendation systems.

5. Zero-Shot and Few-Shot Learning

A pre-trained deep learning model is made to generalize on a category of samples using a machine learning technique called "zero-shot learning. "Zero-shot learning is based on the premise that just as humans naturally discover similarities Between data classes, machines can be trained to do the same.
The primary goal of zero-shot learning is to gain the capacity to predict outcomes without training samples; the machine must be able to identify objects from classes that were not taught during training. The foundation of zero-shot learning is knowledge transfer, which is already present in the training instances.
To forecast a new class of unseen data, zero-shot learning is suggested as a way to learn intermediate.
Semantic Layers and Attributes [16]

The Zero Shot Learning working principles are listed below.

1. Recognizing Features: The computer learns about the key characteristics or attributes that characterize various objects rather than merely learning from instances. For instance, it might be discovered that cats have fur, whiskers, and sharp claws if it is studying animals.
2. Generalization: After learning these characteristics, it can utilize them to identify novel objects that it has never seen before. For example, it can be inferred that a new animal with fur and whiskers is probably a cat if it is aware that cats are typically those animals.
3. Using Clues: The computer occasionally receives extra data to aid in its comprehension of novel concepts. These could be labels or descriptions that explain the characteristics of several categories.
4. Testing: Lastly, we test the computer's ability to identify novel objects. We show it pictures or descriptions of objects it hasn't been trained on, and we test its ability to recognize them accurately using the features it has learned.

Applications: General-purpose generative models like GPT-4 and DALL-E.

5.1 Few-shot learning

In contrast to the approach of feeding huge amounts of data, "few-shot learning" refers to feeding models with relatively little data. The finest example of a meta-learning shot is few-shot learning, which is trained on several related tasks during the meta-training phase to enable good generalization on unseen data using a limited number of samples. Importance of Few Shots Learning.

1. Reducing data collection: Few-shot learning lowers computing and data collection costs by using less data to train the model.
2. It might be difficult to create predictions when there is not enough data for supervised or unsupervised machine learning methods; few-shot learning is highly useful in these situations.
3. After seeing a few samples, humans can quickly classify various handwritten characters; however, a

doi: 10.32622/ijrat.124202408

machine needs a large amount of data to learn how to recognize these handwritten characters. Computers are supposed to learn from a small number of examples, just like people, in a test known as "few-shot learning."

4. Few-shot learning can be used to teach machines about rare diseases. Using a relatively tiny quantity of data, they employ computer vision models to classify the abnormalities using few-shot learning.

Applications of Few-Shot Learning: Computer vision, Natural Language Processing, Robotics, Audio Processing

III. GENERATIVE AI APPLICATION

In settings where a thorough understanding of AI or data science may be lacking, generative AI proves to be a powerful catalyst for organizational transformation. Because of its remarkable capacity to accelerate the implementation of AI applications, it can be accessed through APIs or prompt engineering even with a small amount of data. Although professional supervision allows for significant flexibility, the effects of generative AI are evident in three main skill categories:

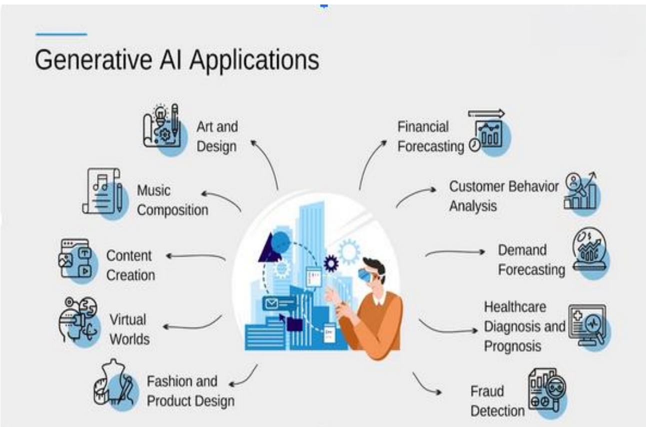

Figure 4: Gen AI Application

A. Media and entertainment

- Given that the media and entertainment sectors mostly perform the same function as the technology—creating original content—they may adopt generative AI in several ways. Short highlight videos of athletic events, assistance in creating and editing visual content, and ease of use with content management systems are all possible with generative AI.
- Produce visual and aural content: Generative AI is capable of producing original video content. By adding graphics, speeding editing, or producing visual effects, this technology can also help you produce visual material more quickly. • Produce highlights for events and sports: Gen AI can produce highlight reels for live events and sports in real-time, enabling fans to produce personalized highlights. Fans might create highlights of a specific play or tournament, for instance.
- Control tags for improved content management: Generative AI can index and categorize large media libraries, which makes it simpler to find the things you need whenever you need them. Generative AI enables you to use conversational language to locate the information or media you're seeking in complicated media, much like in our manufacturing example above.

B. Increasing Productivity

- Generative AI is excellent at increasing output and speeding up repetitive or manual operations. Its function in simplifying these processes, which range from automating email composing and coding to summarizing intricate documents, greatly enhances overall operating efficiency.

C. Personalizing Experiences

- One notable feature of generative AI is its ability to customize information and content for particular target audiences. Technology is crucial for creating engaging and customized experiences, whether it is creating chatbots for individualized user interactions or creating focused marketing plans based on the subtle behavioral patterns of specific clients[13]

D. Health care and pharmaceuticals

Generative artificial intelligence has applications for all parts of the health care and pharmaceutical industry, from discovering and developing new life-saving medicine to personalizing treatment plans for individual patients to creating predictive images for charting disease progression[2]. Some of the possibilities for generational AI in health care include:

- Improving medical images: Generative AI can synthesize, reconstruct, enhance, and provide reports about medical images, including MRIs and X-rays. Even new photos that show the progression of a disease over time can be created using this technology [3]. • Finding new medications: Through a related discipline known as generative design, researchers can utilize generative artificial intelligence to study and create novel medications. According to Gartner, generative design principles will be used in 30 percent of new medications developed by researchers in 2025 [1]. • Make duties easier with patient information and notes: Medical staff members record and document patient treatment. Generative AI is more efficient than humans at finding important details in medical records, creating transcripts of vocally recorded notes, and creating summaries of patient information.
- Personalized treatment: Generative AI can provide a personalized treatment plan based on a great deal of patient data, such as genetic testing and medical pictures.

doi: 10.32622/ijrat.124202408

E. Advertising and marketing

Professionals in the advertising and marketing industries can benefit greatly from generative artificial intelligence in a variety of ways, including creating the text and graphics required for marketing or coming up with innovative ways to communicate with consumers. Examples of generative AI applications in marketing and advertising include the following:

- Produce marketing text and visuals: Marketing experts can utilize generative AI to produce branded, consistent text and images for use in campaigns. Additionally, this technology provides translation capabilities to expand your marketing message into other markets. By 2025, 30 percent of outbound marketing content will be created by marketing experts using generative AI, according to Gartner [1].
- Provide tailored recommendations: Generative AI aids in the development of strong recommendation engines that assist users in finding new goods they might find appealing. Customers can participate more actively in this process thanks to generative AI.
- Write product descriptions: Generative artificial intelligence can assist with laborious or time-consuming content requirements, such as writing product descriptions, in addition to dazzling advertising campaigns.
- Improve search engine optimization: generative AI can be used by SEO experts to generate content drafts or for tasks like image tags and page titles. Additionally, you might utilize a service like Bard or ChatGPT to suggest content modifications that would raise your SEO rating.

F. Manufacturing

Professionals in manufacturing can utilize generative AI to find ways to increase productivity, predict maintenance requirements before they become issues, assist engineers in producing better designs more quickly, and build a more robust supply chain. Let's investigate these possible production fixes:

- Quickening the process of design: By using generative AI to generate design concepts and ask the AI to evaluate them according to project restrictions, engineers and project managers can complete the design process considerably more quickly.
- Offer intelligent equipment maintenance solutions: By using generative AI to monitor heavy machinery performance based on past data, maintenance specialists may be able to identify issues before the machine breaks down. Additionally, generative AI can suggest regular maintenance plans.
- Enhance the supply chain: By conversing with the technology to sift through a large volume of transactional or product data, you may utilize generative AI to identify the root cause of issues in the supply chain. Delivery schedules and supplier recommendations can also be produced with the use of generative AI.

G. Software development

Generative AI can give a software development team the tools they need to write and optimize code more quickly and with less programming language expertise. Here are some instances of how generative AI is being used in software development:

- Code generation: With generative AI, programmers may write, optimize, and auto-complete code. Code blocks can be generated by generative AI by comparing them to a library of related data. Similar to how auto-complete functions on a smartphone when texting, it may also anticipate the remaining code a developer starts typing.
- Programming language translation: Developers may find generative AI useful for interacting with software without the need for a programming language. The translation would be done by the generative AI.
- Automate testing: Using generative AI, developers can enhance their automated testing procedures to identify possible issues and carry out testing sequences more quickly than with other AI techniques. Generative AI can generate test cases and understand the software's logic and user interaction.

IV. FUTURE OF GENERATIVE AI

Generative AI has a bright future ahead of it, one that will transform both technological and social paradigms. Here, we list the main developments and patterns that could influence generative AI in the future:

A. Large Language Model (LLM) advancements

As demonstrated by OpenAI's GPT series, the ongoing development of LLMs represents a revolutionary shift towards increasingly complex and context-aware generating capabilities. Higher degrees of natural language comprehension, finely tuned conversation dynamics, and a more sophisticated approach to content creation are just a few of the advancements anticipated by this progression[10]

These predicted developments in LLMs point to a day when generative AI will be able to respond with greater contextual awareness and understand linguistic nuances at a higher level, resulting in more precise, contextually relevant, and nuanced content production. The continued advancement of LLMs is crucial to expanding the capabilities of generative AI and holding out the prospect of a time when language models will be able to communicate with users in a way that reflects a greater understanding of context, nuances, and the complexities of human communication.

B. Multimodal AI Integration

Generative AI is moving in the direction of smooth multimodal AI integration. It is expected that generative AI models will eventually be able to seamlessly integrate data from a variety of modalities, including text, images, and audio. A significant step forward, this integration opens the door to the creation of interactive and all-encompassing generative systems [9]. These cutting-edge models will soon

doi: 10.32622/ijrat.124202408

show off their amazing ability to produce information in a variety of media formats at once, bringing text, images, and sounds together pleasingly. In addition to increasing the adaptability of generative systems, the integration of several modalities creates new opportunities for producing immersive, rich content experiences that engage users across multiple senses and go beyond conventional limits [13].

C. Enhanced Customization and Control

There is a noticeable trend toward giving Enhanced Customization and Control more importance as generative AI systems become more widespread. As a result, there is a greater focus on giving consumers more control over the outputs produced by these systems and sophisticated customization possibilities. With this augmentation, instructions are refined subtly, users can modify their preferred styles, and the generated content's specificity.

Can be fine-tuned. The main objective is to give users a more customized and individualized experience so they can have more control over the type and attributes of the material produced by generative AI systems. This pattern demonstrates a dedication to respecting personal choices, encouraging user agency, and improving generative technologies' flexibility to satisfy a range of user requirements and expectations.

D. Ethical and Bias Mitigation

Ethical and bias mitigation is a crucial requirement in generative AI. In the future, it will be crucial to address biases in generating outputs and ethical issues head-on. Implementing controls to stop the inadvertent amplification of biases included in training data should be a top priority for developers.

This dedication is motivated by the goal of promoting the ethical and responsible application of generative models, making sure that the technology complies with moral principles and refrains from reinforcing any biases that could be present in the data. By encouraging equity, openness, and ethical considerations in the creation and application of generative technologies, the future of generative AI envisions a proactive and diligent approach to reducing ethical difficulties.

E. Domain-Specific Generative Models

The development of Domain-Specific Generative Models is a new trend in generative AI. According to this trajectory, more specialized generative models that are painstakingly designed for certain domains or sectors will be produced. It is expected that these models will surpass generalized skills, demonstrating a deeper comprehension of the particular context and subtleties inherent in their assigned sectors. More accurate, customized, and domain-specific content creation is anticipated as a result. These specialized generative models seek to produce outputs that are not only contextually accurate but also sensitive to the particular requirements and complexities of the targeted domain by closely aligning with the nuances of specific industries. This is a significant step towards increased relevance and applicability in a variety of professional sectors.

F. Real-Time Applications

There is a paradigm change in generative AI toward interactive use cases as it moves toward real-time applications. Real-time content production during live conversations, dynamic visual element customization, and on-the-fly response generation adapted to changing situations are all examples of the instantaneous and dynamic involvement that the future promises[5]

With this development, generative AI can now easily adjust and react in real time to the dynamic nature of human interactions, marking a break from static and preset outputs. Real-time applications have the potential to completely transform the way generative technologies are incorporated into live scenarios across a variety of sectors. This trend reflects a desire to improve user experiences by encouraging immediacy, responsiveness, and adaptability.

G. Collaborative and Creative Tools

Collaborative and creative tools will be significantly shaped by generative AI. In the future, it is expected that these technologies will enable smooth human-AI collaboration, promoting synergy in content production, design ideation, and brainstorming across a variety of creative fields. The goal is to establish a collaborative and participatory ecosystem where generative technologies work as innovation catalysts and enhance human creativity. It is anticipated that future tools will help close the gap between human creativity and AI skills, providing a healthy partnership that enhances creative processes and produces original, inventive results. This development signifies a paradigm shift in creative workflows, as generative AI plays a crucial and complementary role in the team's creative process[8]

H. Continued Integration into Industries

Generative AI is poised to undergo more industry integration, bringing with it revolutionary changes to workflows and the automation of repetitive and creative jobs. It is anticipated that generative technologies will be widely adopted in a variety of industries, including design, healthcare, education, and entertainment.

Significant breakthroughs, process simplification, and the introduction of creative solutions within different industries are all potential outcomes of this combination. Organizations from a variety of industries hope to increase productivity, encourage creativity, and open up new avenues by utilizing generative AI's capabilities. This represents a paradigm shift in the way generative technologies are used to handle opportunities and difficulties unique to a given business.

Therefore, the potential for transforming technological and societal paradigms is enormous for generative AI. In addition to technological advancements, this vision involves a more thorough, ethical, and individualized integration of AI into our daily lives and industries.

doi: 10.32622/ijrat.124202408

V. CONCLUSION

A thorough and methodical literature assessment of current developments in the field of generative AI is explained in this paper. In particular, it thoroughly examines a variety of techniques in the field of generative artificial intelligence, such as transformer-based models, diffusion models, generative adversarial networks, variational autoencoders, and their developments for particular uses. The paper also discusses several applications of Gen AI that help identify particular research areas. Future scope provides a good notion to prove better in this generative sector. It is also evident that as we move forward into this exciting new future, we must continue to be dedicated to ethical and responsible AI development while simultaneously creating these more sophisticated techniques for generative AI.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] A. Creswell, T. White, V. Dumoulin, K. Arulkumaran, B. Sengupta, and A. A. Bharath, "Generative adversarial networks: An overview," *IEEE Signal Process. Mag.*, vol. 35, no. 1, pp. 53–65, 2018.

[2] A. Esteva, A. Robicquet, B. Ramsundar, V. Kuleshov, M. DePristo, K. Chou, C. Cui, G. Corrado, S. Thrun, and J. Dean, "A guide to deep learning in healthcare," *Nat. Med.*, vol. 25, no. 1, pp. 24–29, 2019.

[3] A. Goncalves, P. Ray, B. Soper, J. Stevens, L. Coyle, and A. P. Sales, "Generation and evaluation of synthetic patient data," *BMC Med. Res. Methodol.*, vol. 20, pp. 1–40, 2020.

[4] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," 2014.

[5] A. Khamparia, D. Gupta, J. J. Rodrigues, and V. H. C. de Albuquerque, "Dcavn: Cervical cancer prediction and classification using deep convolutional and variational autoencoder network," *Multimedia Tools Appl.*, vol. 80, pp. 30399–30415, 2021.

[6] D. P. Kingma, T. Salimans, R. Jozefowicz, X. Chen, I. Sutskever, and M. Welling, "Improved variational inference with inverse autoregressive flow," in *Adv. Neural Inf. Process. Syst.*, vol. 29, D. Lee, M. Sugiyama, U. von Luxburg, I. Guyon, and R. Garnett, Eds., Curran Associates Inc., 2016.

[7] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," 2013.

[8] S. Kollem, K. R. Reddy, and D. S. Rao, "A novel diffusivity function-based image denoising for MRI medical images," *Multimedia Tools Appl.*, vol. 82, no. 21, pp. 32057–32089, 2023.

[9] L. Kumar and D. K. Singh, "A comprehensive survey on generative adversarial networks used for synthesizing multimedia content," *Multimedia Tools Appl.*, vol. 82, no. 26, pp. 40585–40624, 2023.

[10] A. Radford, K. Narasimhan, T. Salimans, I. Sutskever, et al., "Improving language understanding by generative pre-training," 2018.

[11] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen, "Improved techniques for training gans," in *Advances in Neural Information Processing Systems*, vol. 29, D. Lee, M. Sugiyama, U. von Luxburg, I. Guyon, and R. Garnett, Eds., Curran Associates Inc., 2016.

[12] P. Vasanthi and L. Mohan, "Multi-head-self-attention based yolov5x-transformer for multi-scale object detection," *Multimedia Tools Appl.*, pp. 1–27, 2023.

[13] T. Verborgh, R. Troncy, J. Gabarro, and R. Van de Walle, "Adding real-time coverage to the Google knowledge graph," in *11th International Semantic Web Conference (ISWC 2012)*, vol. 914, pp. 65–68, Citeseer, 2012.

[14] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," in *Adv. Neural Inf. Process. Syst.*, vol. 27, Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K. Weinberger, Eds., Curran Associates Inc., 2014.

[15] R. Tahir, K. Cheng, B. A. Memon, and Q. Liu, "A diverse domain generative adversarial network for style transfer on face photographs," 2022.

[16] A. Tlili, B. Shehata, M. A. Adarkwah, A. Bozkurt, D. T. Hickey, R. Huang, and B. Agyemang, "What if the devil is my guardian angel: Chat GPT as a case study of using chatbots in education," *Smart Learning Environments*, vol. 10, no. 1, p. 15, 2023.

[17] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in *Adv. Neural Inf. Process. Syst.*, vol. 30, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds., Curran Associates Inc., 2017.

AUTHORS PROFILE

Mrs. Anagha Abhijit Jawalkar, presently working as an Assistant Professor at D Y Patil College of Engineering, Akurdi Pune, Maharashtra, India. She received her ME(CSE) degree from Savitribai Phule Pune University, in year 2015. Her research interests include Generative AI, Data Science, and Machine Learning.

Dr. Suwarna Gothane, presently working as an Associate Professor at D Y Patil College of Engineering, Pune, Maharashtra, India. She received her Ph. D. (CSE) from Sant Gadge Baba Amravati University, Amravati in the year 2019, her M.E. (CSE) degree from P.R.M.I.T&R, Amravati in the year 2012, and her B.E. (CSE) degree from H.V.P.M C.O. E & Technology. Her research interests include Machine Learning, Data Science, and Artificial Intelligence.

doi: 10.32622/ijrat.124202408