

Exploring the Concept of Generative Artificial Intelligence: A Narrative Review

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Abstract: This paper provides a narrative review of Generative Artificial Intelligence, exploring its evolution, underlying concepts, and diverse applications across various industries. The review is conducted by searching google and google scholar using relevant keywords which in turn leads to different published articles from different websites and databases. The introduction establishes the growing significance of AI in human lives and highlights the rise of Generative AI as a powerful force in creating, innovating, and envisioning. The paper delves into different generative AI models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Recurrent Neural Networks (RNNs), Transformer-based Models, and Diffusion Models. Foundation Models, such as BERT and GPT, are introduced as adaptable models trained on broad data for diverse downstream tasks. The significance of LLMs in Natural Language Processing (NLP) and Computer Vision is emphasized, detailing their impact on text understanding, generation, translation, and information retrieval. The benefits and challenges of LLMs, ranging from natural language understanding to content moderation, are discussed, addressing concerns such as bias, ethical considerations, misinformation, and privacy. The paper concludes with an exploration of the application of Generative AI and LLMs in healthcare and business operations, showcasing their potential in personalized treatment plans, drug discovery, medical imaging, customer support automation, content creation, marketing, human resource automation, and software engineering.

Keywords: generative; artificial; intelligence;

I. Introduction

There is no doubt that Artificial Intelligence (AI) has affected every part of human lives. Not just our lives, but our planet and some neighboring ones. In the past decade, one significant and important part of AI that is in the raise with great future potentials is Generative AI. This is due to its ability of creating, innovating and envisioning [1].

As the name implies, Generative AI is like the artist of the AI world, creating/generating things that seem almost human-made. Generative AI describes models that can be used to create new content, including audio, code, images, text, simulations, and videos based on a vast pre-trained data. Recent breakthroughs in the field have the potential to drastically change the way we approach content creation [1]. One remarkable achievement in the world of generative AI is the birth of Large Language Models (LLM). They are amazing at understanding and creating human-like text. Most recent ones like GPT-3, GPT-3.5 and GPT-4 have opened up a new realm of possibilities, turning what we initially think as imaginary world into reality. One can think of them as super-smart language wizards [2].

This paper gives a review on generative AI with spotlight on large language models. The aim is to provide a comprehensive understanding of the underlying concepts, historical perspective on the evolution of generative AI, diverse application of generative AI across various domains, ethical considerations and challenges associated with these technologies and future trajectories.

II. Generative Ai

Generative artificial intelligence encompasses deep learning models that, through analysis of raw data, acquire the capability to produce statistically likely outputs in response to prompts. These models operate by constructing an abstracted representation of their training data, utilizing this representation to synthesize novel outputs that bear resemblance to, but are distinct from, the original data set [2]. Fundamentally, generative AI is concerned with the development of models capable of autonomously generating original content. These models facilitate the production of diverse data types, including images, text, and audio, thereby enabling machines to exhibit a degree of creative autonomy beyond explicit programming [1]. Employing neural networks, generative AI models discern patterns and structures within existing data to facilitate the creation of unique content. Training methodologies encompass unsupervised and semi-supervised learning paradigms [3]. The emergence of generative AI has significantly transformed human-technology interaction, marking a shift from data processing to autonomous content creation. This transformative capacity has catalyzed the development of previously unforeseen applications, establishing generative AI as a critical component of the contemporary technological landscape [1]. Fig 1 shows how experts categorized generative AI models using an axiomatic diagram.

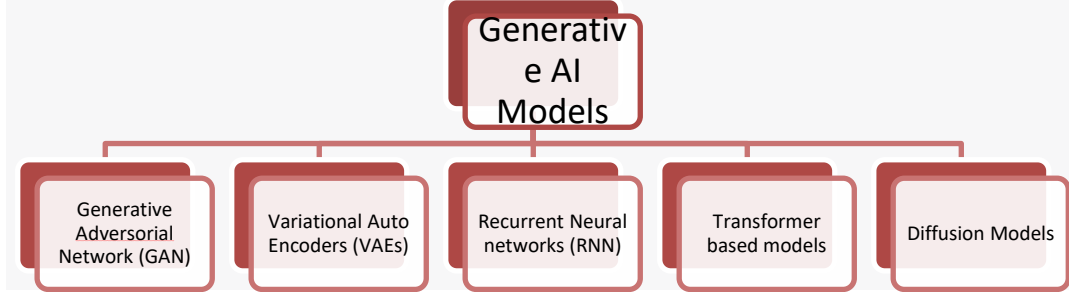


Fig 1: Axiomatic diagram of generative AI models

Generative Adversarial Networks (GANs):

Generative adversarial networks (GANs) offer a methodology for acquiring deep representational learning, mitigating the reliance on extensively annotated training datasets. This is accomplished through the derivation of backpropagation signals via a competitive framework involving two interconnected neural networks [4]. The GAN architecture employs a dual-network configuration: a generator network, tasked with the synthesis of novel data instances, and a discriminator network, designed to differentiate between generated and authentic data samples. This adversarial training paradigm involves the concurrent optimization of both networks, wherein the generator refines its output quality while the discriminator enhances its discriminative accuracy. This iterative process continues until the generated data becomes indistinguishable from the real data distribution [3]. The learned representations derived from GANs find utility across diverse applications, including image synthesis, semantic image manipulation, style transfer, super-resolution imaging, and classification tasks [5]. The fundamental concept of GANs is visually represented in Fig 2.

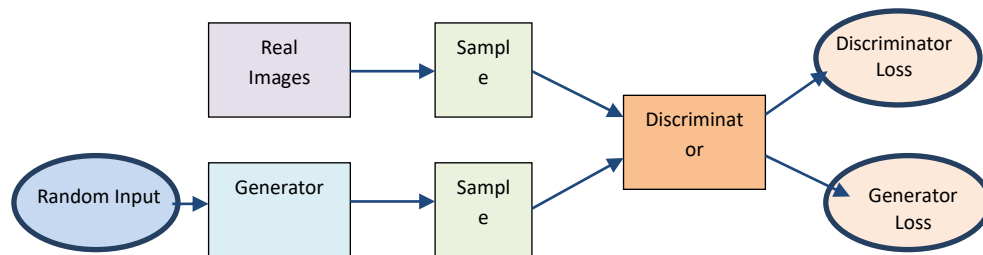


Fig 2: A description of GAN model [6]

Variational Auto encoders (VAEs):

Variational autoencoders (VAEs) are comprised of two interconnected neural networks, commonly designated as the encoder and decoder. The encoder network transforms input data into a lower-dimensional, condensed representation. This compressed representation aims to retain essential information necessary for the decoder to reconstruct the original input, while simultaneously filtering out extraneous details. The collaborative function of the encoder and decoder networks is to learn a streamlined and efficient latent representation of the data. This learned representation facilitates the sampling of novel latent vectors, which can subsequently be processed through the decoder to generate new data instances [3].

VAEs have become a prominent methodology for unsupervised learning of complex data distributions. Their popularity stems from their reliance on standard function approximators, specifically neural networks, and their trainability through stochastic gradient descent. VAEs have demonstrated significant potential in the generation of diverse and intricate data types, including handwritten digits, facial imagery, house numbers, CIFAR image datasets, physical scene models, segmentation maps, and predictive modeling of future states from static images [7]. The architectural framework of a VAE model is depicted in Fig 3.

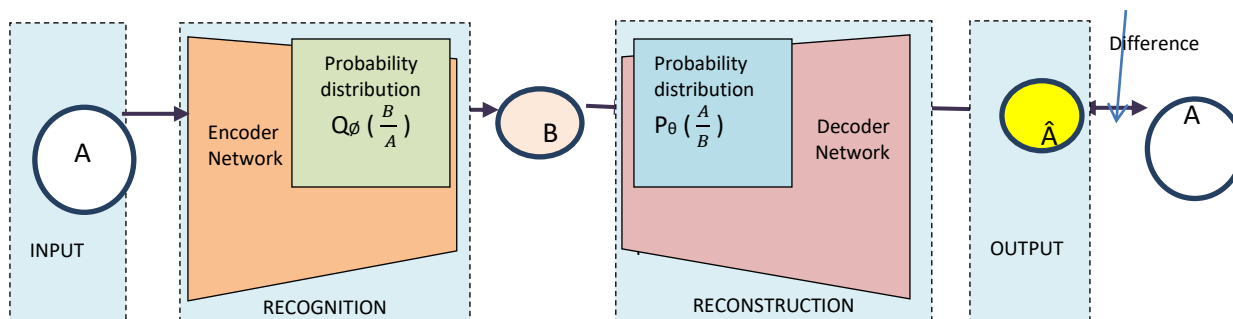


Fig 3: An illustration of VAE model [8]

Recurrent Neural Networks (RNNs):

Recurrent neural networks (RNNs) are a specialized class of neural networks designed to process sequential data, such as natural language sentences or time-series data. This is achieved through the implementation of feedback connections, wherein the network's output at each time step is incorporated as input alongside the subsequent data point. This feedback mechanism enables the network to retain information from previous time steps, facilitating the processing of subsequent outputs. This iterative processing paradigm is the basis for the network's designation as a recurrent neural network [9].

RNNs can be employed for generative tasks by predicting subsequent elements within a sequence based on preceding elements. However, their capacity to generate extended sequences is constrained by the vanishing gradient problem. To mitigate this limitation, advanced RNN variants, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, have been developed [10]. RNNs are the type of artificial neural network used in applications such as Apple's Siri and Google's voice search. The network's internal memory, which facilitates the retention of past inputs, renders it suitable for tasks such as stock price prediction, text generation, transcription, and machine translation [11]. The architecture of a recurrent neural network is illustrated in Fig 4.

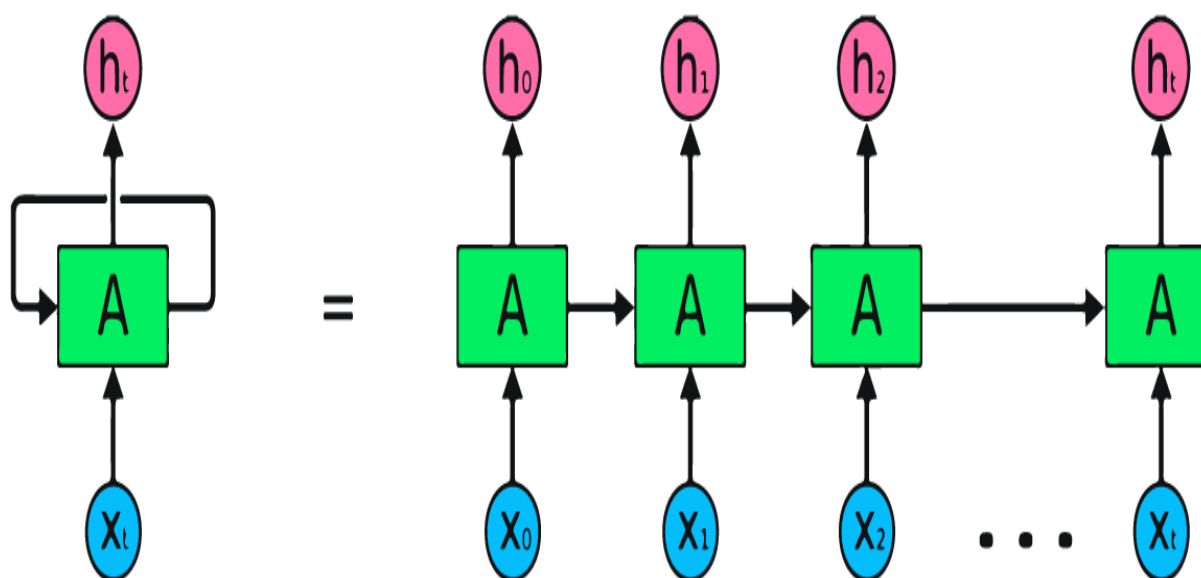


Fig 4: A depiction of RNN [11]

Transformer-based Models:

The Transformer architecture represents a significant deep learning model that has achieved widespread adoption across diverse domains, including natural language processing (NLP), computer vision (CV), and speech processing. Initially proposed as a sequence-to-sequence model for machine translation, subsequent research has demonstrated the capacity of Transformer-based pre-trained models (PTMs) to attain state-of-the-art performance across a spectrum of tasks. Consequently, the Transformer architecture has become the predominant model in NLP, particularly for PTMs [12].

Introduced in 2017 [13], the Transformer model rapidly transformed the landscape of natural language processing. Models such as GPT and BERT, which leverage this architecture, have significantly outperformed previous state-of-the-art networks. The substantial performance gains achieved by Transformer-based models have led to their widespread adoption in contemporary cutting-edge research [12]. Unlike recurrent neural networks, which process sequential data iteratively, Transformers are designed to process sequential input data non-sequentially.

Two key mechanisms contribute to the efficacy of Transformers in text-based generative AI applications: self-attention and positional encodings. Self-attention layers assign weights to each element of the input sequence, reflecting the importance of each element within the context of the entire sequence. Positional encodings provide a representation of the order in which input words occur, thereby enabling the model to capture temporal relationships [13].

A Transformer model consists of multiple interconnected Transformer blocks, or layers. These blocks typically include self-attention layers, feed-forward layers, and normalization layers, which collectively process and predict streams of tokenized data, encompassing text, protein sequences, and image patches [3]. The architectural framework of a Transformer model is depicted in Fig 5.

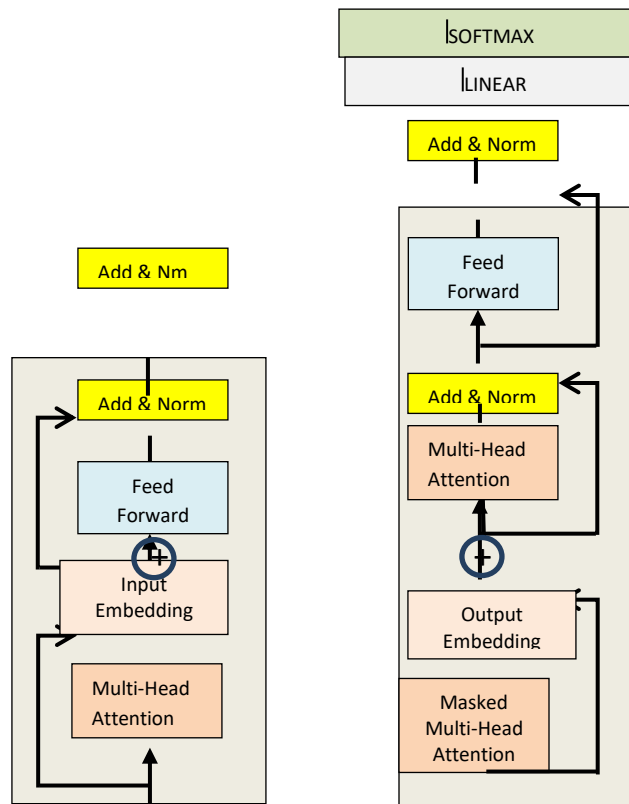


Fig 5: An illustration of transformer model [13]

Diffusion Models

Diffusion models represent a class of generative models employed for the synthesis of data that closely approximates the distribution of their training datasets. These models function by iteratively introducing noise into images and subsequently learning to reverse this process, thereby enabling the generation of novel and diverse high-resolution images that exhibit statistical similarity to the original training data [14]. Diffusion models possess significant potential due to their capacity to generate highly detailed and diverse images, with applications spanning various domains, including drug discovery, virtual reality, and content creation. Furthermore, diffusion models offer distinct advantages over alternative generative technologies, such as GANs and VAEs [15]. They exhibit enhanced training stability, mitigating issues such as mode collapse and vanishing gradients. Moreover, the denoising process inherent to diffusion models facilitates the learning of complex and nuanced data patterns, providing a valuable tool for uncovering and exploiting intricate relationships within datasets [14], [15]. An illustrative representation of a diffusion model is presented in Fig 6.

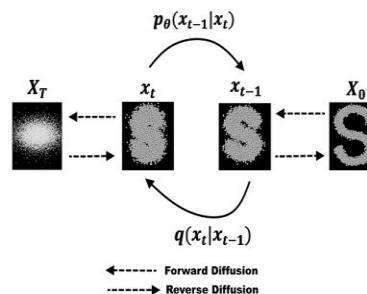


Fig 6: An illustration of diffusion model [15]

Foundation Models

In 2021, Bommasani et al. [17] introduced the term "foundation models," defining them as models trained on extensive datasets, typically utilizing self-supervised learning at scale, which can be adapted, through fine-tuning for example, to a diverse range of downstream tasks. Notable examples include BERT, GPT-3, and CLIP. While the concept of foundation models is relatively recent, their technological basis is rooted in established deep neural network and self-supervised learning techniques that have been developed over several decades.

Foundation models trained on textual data can be applied to solve various text-related problems, such as question answering, named entity recognition, and information extraction. Similarly, models trained on image data can address tasks related to image captioning, object recognition, and image search. The applicability of foundation models extends beyond text and images, encompassing training on diverse data modalities, including audio, video, and three-dimensional signals. These models provide a robust foundation for addressing a wide array of computational tasks [16].

Pai (2023) [16] identifies three primary motivations for the development and utilization of foundation models:

1. **Unified Modeling:** Foundation models offer a highly versatile approach, obviating the need for task-specific models. This "all-in-one" characteristic simplifies the development process by enabling a single model to address a multitude of problems.
2. **Simplified Training:** Foundation models facilitate training due to their reliance on self-supervised learning, which eliminates the dependence on labeled data. Moreover, adaptation to specific tasks requires minimal effort. In contrast to traditional supervised learning, which necessitates extensive labeled datasets, foundation models can achieve high performance with limited examples.
3. **Enhanced Performance:** Foundation models contribute to the development of high-performance models. State-of-the-art architectures for various tasks in natural language processing and computer vision are built upon these foundational models.

Foundation models are broadly classified into 2 types depending on the type of data they are trained on. Fig 7 shows an axiomatic diagram that shows the different classification of foundation models.

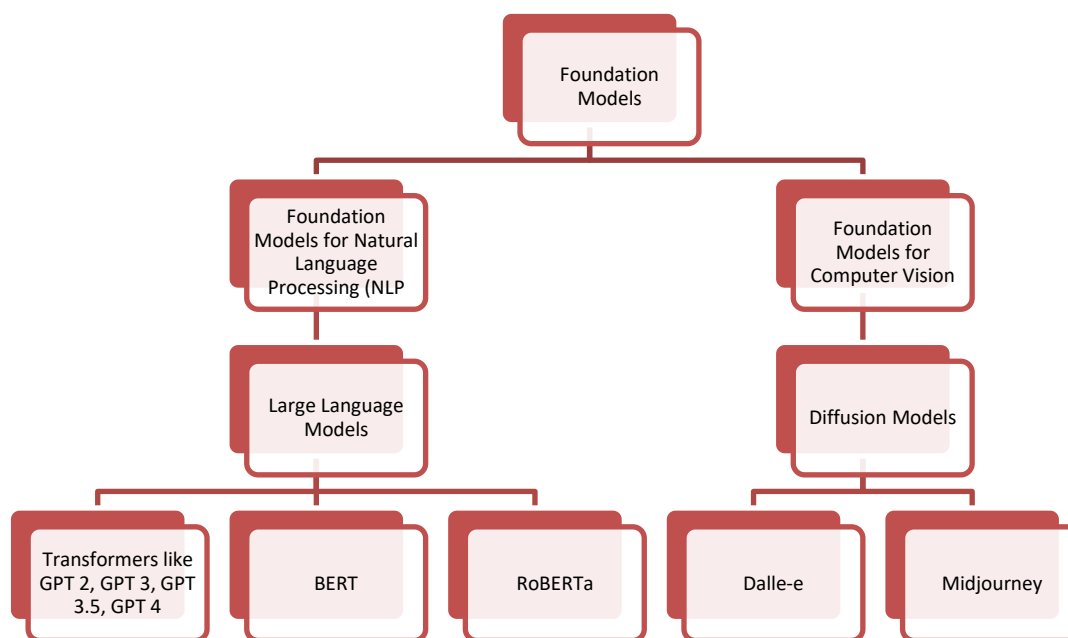


Fig 7: Axiomatic diagram for foundation models

Foundation Models for Natural Language Processing

Large Language Models (LLMs) are the Foundation models for Natural Language Processing. Large Language models are trained on massive amounts of datasets to learn the patterns and relationships present in the textual data. The ultimate goal of LLMs is to learn how to represent the text data accurately. The powerful AI technologies in today's world rely on LLMs. For example, ChatGPT uses the GPT-3.5 as the Foundation model and AutoGPT, the latest AI experiment is based on GPT-4. Examples of Foundation models for NLP include Transformers, BERT, RoBERTa, variants of GPT like GPT, GPT-2, GPT-3, GPT-3.5, GPT-4 and so on [16]and [17]. In this paper, our focus is more on large language models, thus, it is explained in detail in the next section

Foundation Models for Computer Vision

Diffusion models are popular examples of Foundation models for computer vision. Diffusion models have emerged as a powerful new family of deep generative models with state-of-the-art performance in multiple use cases like image synthesis, image search, video generation, etc [16]. They have outperformed auto encoders, Variational Autoencoders and GANs with its imagination and generative capabilities [17].

The most powerful text to image models like Dalle 2 and Midjourney uses the diffusion models behind the hood. Diffusion models can also act as Foundation models for NLP and different multimodal generation tasks like text to video, text to image [16]and [17].

Large Language Models

Language serves as a foundational instrument for human communication and self-expression, and similarly, effective communication is paramount for machines in their interactions with humans and other systems. Large Language Models (LLMs) represent advanced artificial intelligence systems engineered to process and generate textual data, with the objective of achieving coherent communication [18], [19].

LLMs are complex algorithmic systems designed to interpret the semantic content of text. They are deployed in a variety of applications, including machine translation, natural language processing, and text comprehension. LLMs function by processing extensive datasets, thereby learning to identify statistical patterns within textual data. These datasets are derived from diverse sources, such as articles, social media posts, and textual documents [20]. The development of LLMs is driven by the increasing need for machines to perform complex language-based tasks, including translation, summarization, information retrieval, and conversational interactions. Recent advancements in language modeling have been largely attributed to deep learning methodologies, innovations in neural architectures such as Transformers, enhanced computational resources, and the availability of internet-derived training data [19].

LLMs operate by analyzing vast corpora of textual data to discern recurring patterns. This data can originate from a wide array of sources, including articles, books, web services, web pages, and conversational transcripts. Data plays a critical role in the training of LLMs; its absence would preclude the model's ability to learn and recognize textual patterns. Consequently, data acquisition and processing are central to LLM development [20], [19].

Neural network architectures are also essential components of LLMs, facilitating the model's capacity to recognize patterns within the data. These architectures may be based on various algorithms, including deep learning and reinforcement learning. Pre-training, wherein the model is trained prior to its application in text comprehension, is crucial for ensuring accurate pattern identification. Transfer learning, which involves training the model on data outside of its original intended domain, contributes to overall model accuracy [20].

The benefits of large language models are numerous. Large Language Models (LLMs) like GPT-3.5 have several benefits, and their applications span a wide range of fields. Some of them are as follows [20] [19] and [21]:

1. **Natural Language Understanding:** LLMs excel at understanding and generating human-like text, enabling them to comprehend and respond to a diverse array of queries and prompts.
2. **Text Generation:** They can generate coherent and contextually relevant text, making them useful for tasks such as content creation, text completion, and creative writing assistance.
3. **Language Translation:** LLMs can be applied to language translation tasks, helping to translate text from one language to another with reasonable accuracy.
4. **Information Retrieval:** Large language models can be used to extract information from a vast amount of text, aiding in tasks like summarization, question-answering, and knowledge extraction.
5. **Chatbots and Conversational Agents:** LLMs serve as the foundation for building sophisticated chatbots and conversational agents capable of engaging in natural and context-aware conversations.
6. **Programming Assistance:** LLMs can assist developers by generating code snippets based on natural language descriptions, making programming more accessible for non-experts.
7. **Education:** They can be employed as educational tools for language learning, providing tutoring, and generating educational content.
8. **Content Moderation:** LLMs can aid in content moderation by identifying and filtering out inappropriate or harmful content.
9. **Research and Exploration:** Large language models can be used to explore and analyze vast amounts of text data, helping researchers uncover patterns, trends, and insights.
10. **Creativity and Innovation:** LLMs have the potential to inspire creativity and innovation by generating new ideas, stories, or perspectives.

Despite their benefits and unending usefulness, LLMs like GPT-3.5, GPT-4, BERT etc. come with certain risks and challenges [21] and [17]. Some of the notable concerns include:

1. **Bias:** LLMs can inherit and perpetuate biases present in their training data. If the training data contains biases, the model may produce biased or unfair outputs, potentially reinforcing stereotypes or discriminating against certain groups.
2. **Ethical Concerns:** The use of LLMs raises ethical questions, especially when it comes to generating content that might be misleading, harmful, or used for malicious purposes. It is essential to consider the ethical implications of deploying these models in different contexts.

3. **Misinformation:** LLMs have the capability to generate text that may be factually incorrect or misleading. This can contribute to the spread of misinformation, and it highlights the importance of ensuring accuracy and reliability in the outputs of these models.
4. **Lack of Understanding:** LLMs may not truly understand the content they generate. They operate based on patterns learned from data but lack genuine comprehension. This can lead to responses that sound plausible but may not reflect a true understanding of the underlying concepts.
5. **Security Concerns:** There is a risk of malicious use, such as generating convincing phishing emails or other forms of social engineering attacks. Ensuring the secure deployment of these models is crucial to mitigate potential risks.
6. **Over-Reliance:** Over-reliance on LLMs without critical evaluation could lead to blindly trusting their outputs, even when they are incorrect or biased. It's essential to use these models as tools and not as infallible sources of information.
7. **Privacy:** There are concerns related to privacy, especially when dealing with sensitive information. Generating text based on personal or confidential data could pose privacy risks if not handled appropriately.
8. **Environmental Impact:** Training and running large language models require significant computational resources, contributing to a high carbon footprint. Addressing the environmental impact of training such models is an ongoing concern.

Researchers and developers are actively working to address these challenges through techniques like bias mitigation, ethical guidelines, and responsible AI practices. It's important to approach the deployment of LLMs with a clear understanding of these risks and to take steps to mitigate potential negative consequences. Ongoing research and community collaboration are essential to improving the safety and reliability of large language models [21] and [17].

Application of Generative AI and LLMs in various industries

The versatile nature of generative AI especially the LLMs makes them valuable assets in numerous industries, streamlining tasks, enhancing productivity, and improving the overall user experience. In this section, we show how Generative AI and LLMs affect health care industry and business industry.

HealthCare

Recent breakthroughs in generative AI and the emergence of transformer-based large language models such as Chat Generative Pre-trained Transformer (ChatGPT) have the potential to transform healthcare education, research, and clinical practice [22]. This section gives a description of the different aspects of healthcare which are affected by generative AI viz:

Personalized Treatment Plans: Personalized medicine aims to provide tailored medical treatments to individual patients based on their genetic, environmental, and lifestyle factors. However, accurately predicting a patient's response to a particular treatment remains a significant challenge due to the system's complexity. By analyzing patient data, generative AI can assist in creating personalized treatment plans based on individual health records, genetic information, and lifestyle factors. This tailored approach can lead to more effective and efficient treatments [23]

Drug Discovery and Development: Drug discovery involves identifying molecules, biologics, or other therapeutic agents that can promote tissue regeneration and functional recovery. The development of drugs is limited by the lack of advanced technologies. Traditional drug development processes can be time-consuming and expensive, as they involve synthesizing and testing a large number of compounds to identify potential drug candidates. Another major concern in drug discovery is ensuring that the potential drug candidates are safe and effective. To overcome these challenges, AI has emerged as a powerful tool that can analyze large datasets of chemical compounds to predict which treatments work best for certain illnesses. It has become possible to detect patterns and associations by analyzing chemical structures and properties, which can help identify potential drug candidates. Generative models can simulate molecular structures, predict potential drug interactions, and streamline the drug discovery process. This significantly reduces the time and costs associated with bringing new medications to market. Examples of AI tools that helps in drug discovery are: DeepChem, DeltaVina, AlphaFold and Chempouter [23] and [24].

Medical Imaging: Generative AI algorithms can help in improving diagnostic accuracy, enhancing image analysis by analyzing medical images, such as X-rays, MRIs, and CT scans, with high precision. This aids in early detection of diseases, provides more accurate diagnoses, and helps clinicians make informed decisions about treatment strategies [25] and [24].

Medical Chatbots: Generative AI can create medical chatbots that provide patients with personalized medical advice and recommendations. They interact with patients, answer queries, and provide information about symptoms, medications, and treatment plans. This enhances patient engagement and support, especially in remote or underserved areas. For example, Babylon Health has developed a chatbot that uses generative AI to ask patients about their symptoms and deliver personalized medical advice [26].

Medical Research and Knowledge Generation: Generative AI models can facilitate medical research by generating synthetic data that adheres to specific characteristics and constraints. Synthetic data can address privacy concerns associated with sharing sensitive patient information while allowing researchers to extract valuable insights and develop new hypotheses [26].

Documentation: Generative AI can significantly enhance the documentation process undertaken by doctors in patient care. It can assist in the automatic generation of detailed and accurate medical notes based on the input provided by healthcare professionals. This technology can streamline and expedite the documentation workflow by suggesting relevant information, completing repetitive tasks, and ensuring consistency in terminology and formatting. Furthermore, generative AI can contribute to the interpretation of unstructured data within patient records, facilitating the extraction of valuable insights for diagnosis and treatment planning. Overall, the integration of generative AI in medical documentation not only improves efficiency but also helps healthcare providers maintain thorough and standardized patient records, ultimately leading to better-informed decision-making and enhanced patient care [26] and [23]. Examples are BayerPharma, HCA healthcare and Meditech [27].

Business Operations

Generative AI has emerged as a transformative force in optimizing business operations across diverse industries. Some of the effects of Generative AI in businesses include the following:

Automate Customer Support: It can transform how businesses interact with their customers and enhance their overall customer experience. It has the ability to create and deploy intelligent chatbots and virtual assistants that can interact with customers in real time. It can be used 24/7 and respond rapidly to all types of customer queries.

Examples of chatbots used for customer support are: Tidio, Freshchat, Zoho SalesIQ, Conversica, Netomi, Intercom, Drift, Jitbit Helpdesk, Kommunicate, Ushur, IBM Watson Assistant [28].

Content Creation: They help in creating contents for advertisement, logos, social media post, audio and video jingles, emails. They create such contents in an excellent and competitive manner which will help in boosting the business. Examples of such generative AI systems are: OwlyWriter AI- textual content, Chat GPT – textual content, Dall-E, Graphics/Images, Mid-Journey – Graphics, Jasper-Ai – textual content, Synthesia – video creation and modification, Murf – Audio generation [29].

Marketing: Effective content creation of generative AI helps in selling the products

Design and Creativity: Generative Ai helps in creating new ideas to boost an enterprise, gives information about market trends. It helps with latest design ideas in Businesses that involves fashion, tailoring, artistry and architecture. Examples of such AI system include all text based and image based generative Ai systems [30].

Human resource Automation: In Big enterprises where there is a high number of staff, generative AI helps in automating human resource activities such as automating job descriptions, resume screening, training materials etc example is ChatGPT [31].

Software Engineering: It helps entrepreneurs/programmers that take contract for software development, update and maintenance in various stages of software development lifecycle. This includes code generation, bug detection and correction, software documentation. It affects standalone systems, websites and mobile apps. Examples of generative AI systems that help in coding are: ChatGPT, OpenAI codex, Tabnine, codeT5, polycoder [32].

Many companies in different countries across the globe including the USA and the UK are using generative AI. When businesses integrate this technology, it helps them sell more and become more successful. This, in turn, has a positive impact on the overall economy by contributing to financial growth. The popularity of generative AI highlights its importance in making businesses more efficient and achieving positive results in different industries [31].

III. Discussion

The paper recognizes the significant impact of Generative AI on various facets of human life and highlights the recent surge in interest, especially with the advent of advanced models like GPT-3, GPT-3.5, and GPT-4. These models are portrayed as innovative language wizards with the ability to create human like text. Various types of generative AI models, such as GANs, VAEs, RNNs, diffusion models and transformers were discussed. Each of these models plays a unique role in generating content, from images to text, and contributes to the broader landscape of AI innovation. The introduction of Foundation Models, exemplified by BERT and GPT, showcases their adaptability for a wide range of tasks across different domains. These models, trained on extensive datasets, serve as versatile tools that can be fine-tuned for various downstream applications in Natural Language Processing and Computer Vision. The review highlights the numerous benefits of LLMs, including their prowess in natural language understanding, text generation, translation, information retrieval, and creative content creation. LLMs, like GPT-3.5 and GPT-4, are depicted as powerful assets with applications spanning diverse fields. The discussion delves into the challenges associated with LLMs, such as biases, ethical concerns, misinformation, lack of genuine understanding, security risks, over-reliance, and environmental impact. These challenges emphasize the importance of responsible AI deployment and ongoing research to address potential negative consequences.

Furthermore, the paper showcases the practical applications of Generative AI and LLMs in industries like healthcare, businesses and education. In healthcare, applications include personalized treatment plans, drug discovery, medical imaging analysis, medical chatbots, and documentation support. The integration of generative AI in healthcare aims to enhance efficiency, accuracy, and patient care. In business operations, it covers areas like customer support automation, content creation for marketing, human resource activities, and software engineering. The integration of these technologies is portrayed as a catalyst for business efficiency and success.

In conclusion, Generative Artificial Intelligence opens up exciting possibilities across various fields and aspect of human lives. While these technologies bring immense benefits, they should be used responsibly while considering ethical rules. As we navigate this era of generative AI, it is crucial to harness its potential for innovation while ensuring that they contribute positively to our society and the way we live and work.

During the preparation of this work the authors used GEMINI in order to PARAPHRASE. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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