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RESEARCH PAPER

Quantum Computing to Enhance Generative AI Models for Advanced Text and Image Creation

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***Abstract*—The use of generative artificial intelligence (GenAI) together with quantum computing is a substantial break-through in the strength of computations, since it provides better performance, scalability, and efficiency. Although traditional GenAI models have achieved success, they are not scalable and can only deal with simple distributions of data or surmount computational bottlenecks. Quantum-enhanced GenAI uses the learnings of quantum mechanics (superposition, entanglement, quantum parallelism) to make computations exponentially faster, data representation more efficient, and generative procedures more optimized than what can be done by classical AI. In this paper, the authors provide an in-depth analysis of quantum generative artificial intelligence, its principles, implementations, and the existing issues. It touches on how quantum generative adversarial networks, quantum Boltzmann machines, and variational quantum circuits are used in better generation of texts and images. The higher computation efficiency, faster learning, and flexible models that QGAI enables offer possible solutions to some unsolvable problems in field of cryptography, materials discovery, financial modeling, and molecular simulation. Nevertheless, the complete potential of QGAI can be achieved only when major issues are addressed, such as shortfalls in quantum hardware and the immaturity of quantum algorithms and problems in the combination of quantum and classical systems. Future research directions are outlined in the study, which should include more scalable quantum algorithms, error-resistant quantum processors, and more developed hybrid frameworks. Issues of ethics and regulations are also touched on to deal with various dangers that might arise due to the misuse of such potent generative technologies by society. This study outlines a bright future of development of QGAI as it proposes that QGAI will push artificial intelligence to new limits in case these challenges are successfully addressed. This will result in groundbreaking innovations in the field of AI, which will cause breakthrough solutions in many industries and fields of science.**

Keywords*—Quantum Computing, Generative Artificial Intelligence (GenAI), Quantum Generative Adversarial Networks (qGAN), Computational Efficiency, Hybrid Frameworks.

I. INTRODUCTION

There has been a tremendous advancement in Generative Artificial Intelligence (GenAI), which has already achieved impressive results in synthesizing texts, images, and videos. Recent architectures, such as Generative Adversarial Networks (GANs), Variational Autoencoders and Transformer-based models have been effective to an extent. But they have limitations to the extent and their efficiency due to their use of classical computational techniques. Large-scale models require a lot of computing power to train and deploy, thus consuming a lot of energy and time.

More computationally efficient approaches are necessary since GenAI applications are being introduced into all different industries such as entertainment and healthcare among others. Quantum computer offers a revolutionary alternative by exploiting quantum mechanical phenomena such as superposition, entanglement and quantum interference. This can become very fast because of downright parallel calculations which are made possible by the fact that qubits can remain in many states at once in contrast to traditional bits. This intrinsic parallelism is an indication of paradigm change related to the generative AI, which may assist in breaking such limitations of conventional technology, allowing to introduce ever more sophisticated and elaborate generative models [1]. This could lead to advances in such areas as synthetic not just scientific research, but also unprecedented generation of data entailing individualized content generation [2]. The increasing exponentiation that artificial intelligence is going through, specifically through the exercise of large language models, has transformed the world of creating content and created formidable pressures on prevailing computing and communication systems [3][4].

The development of such innovative generative AI systems, as ChatGPT and DALL-E, triggered the development of a new wave in the synthesis and manipulation of digital information, especially when it comes to the creation of lifelike images, audio, and text [5]. This technological feat, which offers the potential to create human-like texts based on the natural language input, is a strong indicator of the radical change in different fields, education and sentiment analysis included [6][7]. In particular, the models are based on deep learning architecture and transformers and are used to create new content that is not part of the data available [5]. This can be utilized in other applications such as data augmentation and sentiment simulation where a generative model can synthesize new data sets or replicate the way humans express sentiment to enhance training and generalization of such other models [8]. It has such an advantage because they can output statistically likely solutions within trends learned during the training on the enormous sets of data, and this makes them handy tools to be used in a variety of applications [9]. Context-sensitivity means the ability of these models to take complex linguistic relationships into account and reflects previously discussed relevant contextually-colored interpretations which cannot be made with simpler models [8]. Generative AI models (Figure 1) can transform both work and communication by generating novel and valuable content based on the training data that can include text, images, and audio [10]. It makes the humans to have direct in the process of creation through text-to-image systems or open communication with transformer-based language models [11]. Since generative AI has a creative capability to create material across a variety of modalities, it is on the frontline worldwide as one of the technologies in the advancement of multimedia production and transformation [5].

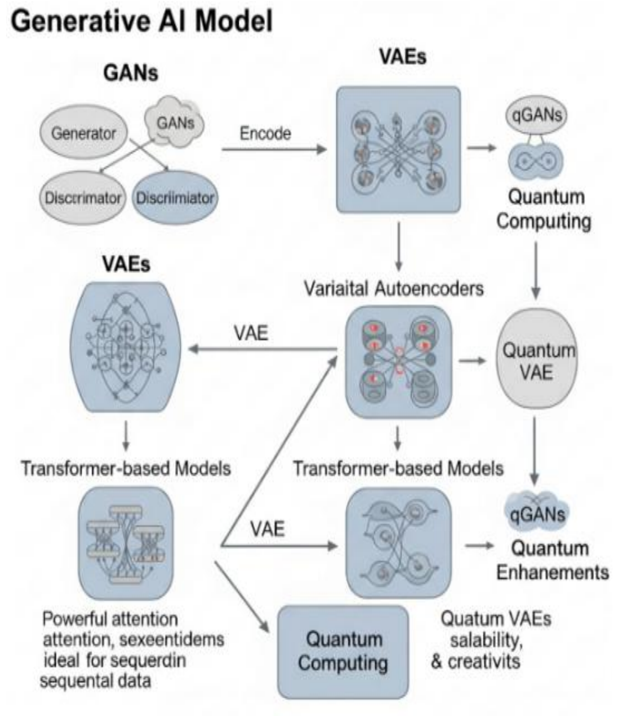

Fig. 1. Generative AI model

New algorithms such as variational QE algorithm, quantum approximate optimization algorithm, and grover search algorithm have been shown to run interesting complex problem optimization and probabilistic problem in a more efficient way. There are possibilities of redefining computing performance and capabilities whenever these quantum strategies are implemented in GenAI frameworks. Although quantum-enhanced AI has the potential to revolutionize AI applications, it is currently faced by some setbacks, such as the sensitivity of quantum hardware available today to noise and the lack of qubit coherence, as well as operational reliability. The scalability is also a considerable barrier to mass use. The current paper discusses these issues by examining the error correction procedures, the noise-tolerant quantum computing algorithms, and the hybrid computational approaches capable of solving the stability and reliability problems via a combination of the classical and quantum processing.

II. Related Work

The fusion of artificial intelligence and quantum computing, in particular, in generative models is a recent area of research. Quantum enhancements of GANs and VAEs have thus far been proposed in many studies, with potential to lead to greater scalability and efficiency. As an example, quantum GANs (qGANs) have been suggested to optimize the models, achieving faster training and using quantum parallelism. Research also implies the use of quantum algorithms, e.g. Grover algorithm and QAOA, in the field of optimization and sampling. Nevertheless, the main challenges to the expected proliferation of quantum-enhanced AI models continue to be the development of quantum hardware and algorithms and the combination of the latter with classical systems. These are associated with handling issues related to error-correcting methods, the hardware limitations of quantum computers and scalability issues arising in quantum-classical combinations [1]. Although it is theoretically correct as well as proven empirically that quantum computing has the potential to carry out machine learning, at a much higher performance than is the case with classical machine learning, the option of quantum information and machine learning has gained popularity as quite a promising direction of quantum computing [2]. Quantum machine learning can generate classical datasets that could be applied to financial risk management, discovery of anomalies, or enrichment of training data [3]. Although several of these quantum algorithms claim to achieve exponentially greater performance than classical computing, they are currently challenging to execute on near-term noisy intermediate-scale quanta computers, and additional study into error-correcting measures and noise immunity methods is needed [4]. In addition, machine learning can also experience a revolution due to the fact that against the background of exponential increase in the ability to process information that quantum computers can offer, it is mainly in the spheres such as text translation and picture recognition where the ability to process will be enhanced exponentially [5]. Quantum algorithms capable of enhancing or fully substituting classical machine learning protocols have been a subject of significant interest to the scientific quantum information community in their ongoing effort to construct these algorithms [6]. Consequently, quantum generative adversarial networks are developed, where quantum concepts are integrated into the conventional mainstream GAN structure [7]. This integration is particularly relevant to the fact that quantum machine learning will be one of the most likely early quantum devices general-purpose applications [7]. Regardless of its implications, most of the implemented algorithms primarily rely on quantum states rather than classic data as training data, which may not be the most significant classical machine applications contrary to popular belief [8]. Since quantum mechanics has a natural tendency to create exotic patterns, quantum computers can potentially compete with the classical systems in certain machine learning scenarios [9]. Hence, the new domain of research is to bridge this gap, and convert classical data to quantum, which will efficiently process and analyze classical data through quantum algorithms [10]. Among the primary advantages of quantum algorithms, it is possible to distinguish the fact that quantum algorithms can lead to exponential speedups of some machine learning algorithms, particularly those with large data sizes being hard to process with conventional methods of computation [11].

Although quantum machine learning might have significant theoretical breakthroughs, it exhibits only testable quantum advantages on datasets motivated by synthetic cryptography in the case that such data are fed to classical models [12]. It is especially so when it comes to generative models, the objective of which is to model complex underlying probability distributions that govern the processes of data generation. Since quantum mechanics is founded on probabilistic amplitudes it would specifically be ideal in this endeavor [13]. Examples of such applications include quantum generative adversarial network that aims to enhance the quality of model generation and accelerate the process of training based on the principles of quantum [1]. Specifically, quantum generative adversarial networks extend the classical GAN framework to incorporate the quantum mechanical aspects in both discriminator and generator units and even in the data [14]. One of the greatest weaknesses of traditional GANs is that they cannot produce discrete data due to the issue of vanishing gradients; in contrast, quantum GANs have the inherent functionality of this nature [15]. All in all, this new direction is likely to avoid the issues related to creating discrete data that standard GANs often experience, potentially leading to generative models that are more robust and flexible. This matters since the volume of data that is currently being stored throughout the whole world is developing at an astounding pace which is approximately 20 percent annually and this is exerting intense pressure on academicians in their endeavor to develop more imaginative and successful machine learning strategies [16]. One of the significant developments in classical machine learning, generative adversarial training applies the gradients of discriminator models to another generative model; this is being extended to quantum in the current project [7]. On that note, quantum GANs facilitate the processing and generation of quantum states directly rather than classical information by adding the quantum operations to both the discriminator and the generator networks [4]. To replicate the quantum states, this adversarial training framework has been altered to quantum data where the generator attempts to deceive the discriminator and the discriminator attempts to determine whether the data (both real and artificial) is genuine or not [17]. In quantum-related applications, such as in the case of condensed matter physics and in quantum chemistry, this quantum version of GANs is mandatory, as it permits exploration of the quantum data distributions and potentially the generation of entirely new quantum states [18]. This system can create high-quality audio, video and image content and also generate synthetic data to help fill up existing datasets [19][20].

III. Generative AI Overview

Generative Artificial Intelligence involves algorithms that are meant to create data in the same way a human would generate content. Compared to the traditional AI that only classifies or predicts based on the input data, generative AI is novel in terms of the output it makes in the form of text, images, videos, and audio. The underlying driving force behind this capability is that the neural network architectures have improved, there is some growth in computing power and immense datasets. Generative Artificial Intelligence involves algorithms that are meant to create data in the same way a human would generate content. Compared to the traditional AI that only classifies or predicts based on the input data, generative AI is novel in terms of the output it makes in the form of text, images, videos, and audio. The underlying driving force behind this capability is that the neural network architectures have improved, there is some growth in computing power and immense datasets. It is an evolving technology that has penetrated to the point of its major models such as Generative Pre-trained Transformer and Generative Adversarial Networks, which have essentially changed the human to computer interaction and workaround on the complex problem solving in different industries [21][22]. The current spread of this technology around the whole world is changing the way we work and communicate, the best examples of which are the models such as DALL-E 2, GPT-4, and Copilot [3]. Such paradigm shift is quite big step forward as compared to the previous AI abilities because now instead of simply evaluating or processing the pre-existing information, the paradigm shift lets the automatic generation of the new material [23][24]. These models learn by training on large amounts of existing data, such as text, photographs and music, in order to produce new material that is both distinctive and statistically consistent with the patterns and structures observed in their training datasets [25]. Generative Adversarial Networks (GANs) are one of the most notable types of generative AI and consist of two antagonistic neural nets: a generator and a discriminator. The discriminator determines whether the data samples that are being generated by the generator are valid. In this process of adversarial training, highly realistic content is generated.

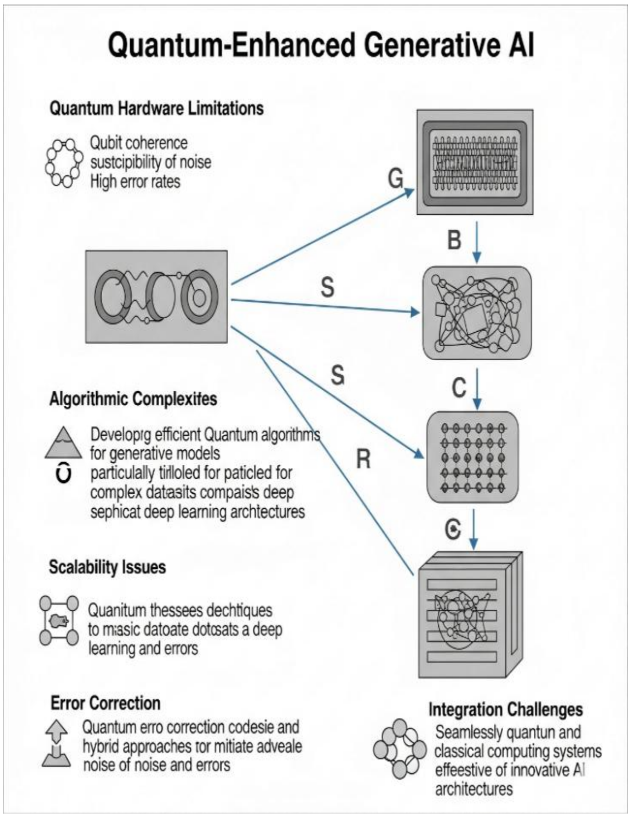

Fig. 2. Quantum-Enhanced Generative AI model

Another important architecture is called Variational Autoencoders (VAEs). They process the input data into a latent structure, and it is then decoded into the input data. VAEs allow the generation of diverse and controlled data through the incorporation of probabilistic modelling and therefore can be used in many tasks such as image synthesis, data compression and anomaly detection [26].

IV. Quantum Computing Overview

Quantum computing offers a major departure in computing methods, and it is based on the utilization of quantum physics to deal with problems that conventional classical systems do not allow in an effective manner. Quantum computers are based on quantum bits (qubits) instead of binary digits (bits) that are involved in classical computers. Qubits are able to be any superposition of 0 and 1 at the same time depending on what state they are in. This enables significant parallelism, and in some applications complex tasks can be computed in a short amount of time [27].

A. Core Principles of Quantum Computing

- Superposition allows qubits to be in more than one state at a time and so distinguish superposition qubits compared to classical bits. Such an aspect enable the paral closing of large datasets on the quantum computers simultaneously.
- Entanglement The states of qubits can be entangled so that they affect each other and this further makes calculations efficient and makes algorithms more reliable.
- Quantum interference helps the algorithms to perform better by enhancing the correct computational pathways as well as inhibiting incorrect ones.

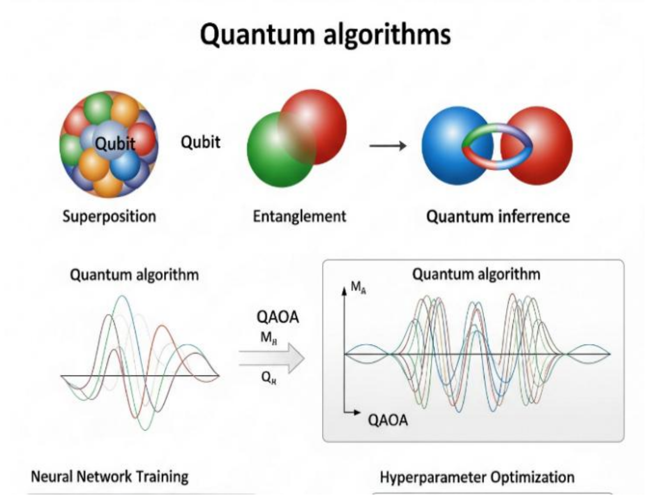

Fig. 3. Quantum-Algorithm Generative AI model

B. Quantum Algorithms and their Advantages

Based on these principles, quantum algorithms (Figure 3) are used to accomplish a better performance in specific attempts. Quantum Approximate Optimization Algorithm proves to be very successful in terms of combinatorial optimization problem solver, enhancing other tasks like training a neural network and hyperparameter optimization [28].

V. Integration of Quantum Computing in Generative AI

The integration of generative AIs with quantum computing introduces a new possibility of enhancing models and computation by efficiency. Quantum algorithms that use quantum parallelism, entanglement and superposition operate at least several times more efficiently than classical systems. The approach of hybrid frameworks, applications of these frameworks in algorithms, and situations are the primary issues of our analysis of integration approaches [29].

VI. Important Applications and Use Cases of Quantum-Enhanced Generative AI

Generative AI enhanced by quantum has a lot to contribute to a number of businesses. It accelerates the drug discovery process in the medical field because it is an accurate simulation of molecular interactions. It improves the risk analysis and optimization in the field of finance. The quantum-enhanced models (Figure 4) also play a significant role in improving cybersecurity through the use of superior cryptographic methods, creation of innovative content, and development of manufacturing [30].

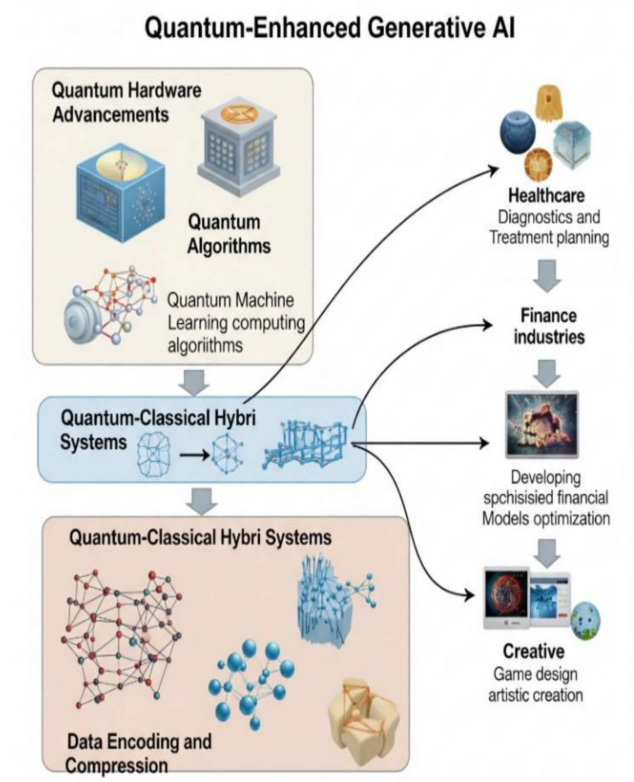

Fig. 4. Quantum-Algorithm Generative AI model

VII. Challenges and Limitations of Quantum-Enhanced Generative AI

Although quantum-enhanced generative AI represents a revolutionary breakthrough, it is affected by the number of issues:

- **Weaknesses of Quantum Hardware:** It turns out that the quantum processor available today is restricted by the number of qubits, noise, and loss of coherence.
- **Algorithmic and Computational Complexity:** Generative AI is quantum computing that is also complex to design and integrate with other classical systems.
- **Scalability and Resource Requirements:** Quantum systems have scaling and resource challenges so it would take a lot of residential resources to manipulate big volumes of data.

VIII. Future Directions

The development of scalable quantum data encoding techniques, fault-tolerant quantum computers, resilient hybrid quantum-classical systems, and on-demand, domain-specific quantum algorithms forms one of the foundations of the future of quantum-enhanced generative AI. New studies are needed to increase used hardware abilities and ensure the reliable use of quantum generative models at the current level [21]. This requires exploring not only what is known, deep down, of sophisticated error correction protocols, but also new quantum architectures capable of sustaining the computational requirements of complex generative applications. Also, the emergence of the Noisy Intermediate-Scale Quantum technology has realized immediate prospects of advancing quantum generative models that can be used as a means of exploiting quantum benefits in other machine learning applications despite hardware limitations at present [22]. The synergistic synthesis of classical and quantum approaches in generative adversarial networks presents potential route to achieve acceleration of training and optimization of model. This method has been especially useful in the generation of classical data which plays critical role in applications like augmenting training data, finding anomalies and financial risk management [23]. Moreover, it has also been found that the application of generative models such as ChatGPT is drifting towards the possibility of its use in sentiment analysis, where generative models can be beneficial in aspects like data augmentation and the manifestation of more subtle instances of sentiment by generating coherent and situation-appropriate text [24]. The integration utilizes the efficiency of big language models to determine and categorize sentiments, passing the typical weaknesses observed when using classical techniques like dealing with negation and modifiers [25].

IX. Conclusion

Quantum-enhanced generative AI is one of the bold shifts in computing powers that find the solution to the weaknesses of classical AI. In the era of quantum computing, the technology is about to transform healthcare, financial, and content creation sectors by providing more user-efficient, accurate, and efficient systems of AI. The full potential of quantum generative AI remains unexplored, but it must be solved by solving existing problems in hardware, algorithms, and scalability to lead to the quantum-leap revolution in the field of AI research and application. The introduction of artificial intelligence and quantum computing or quantum AI is considered a big step that has the potential of offering unprecedented processing and advanced intelligence in many sectors. This fusion can profit both lines of work in considerable ratios, where it may solve the computationally intensive problems that are not feasible in the current traditional methods. This relationship is particularly applicable in exercising advanced problem-solving and the rapid processing of data and intelligent automation. To increase the speed of processes such as iterative training and data distillation, the new field seeks to exploit quantum phenomena, such as entanglement and superposition, to make more powerful and effective algorithms of machine learning. The quantum generative adversarial networks represent one of the most interesting methods in this evolving atmosphere. They aim at accelerating the process of training GAN with the help of special features of quantum, which gives a new perspective on the enhancement of generative models. These quantum innovations are specifically aimed at solving inherent problems of classical generative adversarial networks, including scalability and convergence problem of the training process, by taking advantage of quantum parallelism and quantum entanglement to enhance better data generation and optimization of the model.

References

[1] S. Nokhwal, S. Nokhwal, R. Swaroop, R. Bala, and A. Chaudhary, "Quantum Generative Adversarial Networks: Bridging Classical and Quantum Realms," arXiv (Cornell University), Jan. 2023. doi: 10.48550/arxiv.2312.09939.

[2] H.-L. Huang, et al., "Experimental Quantum Generative Adversarial Networks for Image Generation," Physical Review Applied, vol. 16, no. 2, Aug. 2021. doi: 10.1103/physrevapplied.16.024051.

[3] A. Vieloszynski, S. Cherkaoui, J. Laprade, O. Nahman-Lévesque, A. Aaraba, and S. Wang, "LatentQGAN: A Hybrid QGAN with Classical Convolutional Autoencoder," arXiv (Cornell University), Sep. 2024. doi: 10.48550/arxiv.2409.14622.

[4] M.-L. Hu, et al., "Quantum Generative Adversarial Learning in a Superconducting Quantum Circuit," Science Advances, vol. 5, no. 1, Jan. 2019. doi: 10.1126/sciadv.aav2761.

[5] H.-Y. Huang, et al., "Power of Data in Quantum Machine Learning," Nature Communications, vol. 12, no. 1, May 2021. doi: 10.1038/s41467-021-22539-9.

[6] A. Perdomo-Ortiz, M. Benedetti, J. Realpe-Gómez, and R. Biswas, "Opportunities and Challenges for Quantum-Assisted Machine Learning in Near-Term Quantum Computers," Quantum Science and Technology, vol. 3, no. 3, p. 30502, Jun. 2018. doi: 10.1088/2058-9565/aab859.

[7] P.-L. Dallaire-Demers and N. Killoran, "Quantum Generative Adversarial Networks," Physical Review A, vol. 98, no. 1, Jul. 2018. doi: 10.1103/physreva.98.012324.

[8] J. Liu, et al., "Towards Provably Efficient Quantum Algorithms for Large-Scale Machine-Learning Models," Nature Communications, vol. 15, no. 1, Jan. 2024. doi: 10.1038/s41467-023-43957-x.

[9] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum Machine Learning," Nature, vol. 549, no. 7671, p. 195, Sep. 2017. doi: 10.1038/nature23474.

[10] S. Pise, A. A. Agarkar and S. Jain, "Unleashing the Power of Generative AI and Quantum Computing for Mutual Advancements," IEEE Conference Publication, IEEE Xplore, 25 Aug. 2023.

[11] J. Tian et al., "Recent Advances for Quantum Neural Networks in Generative Learning," IEEE Journals & Magazine, IEEE Xplore, 1 Oct. 2023. M. Xu, et al., "Generative AI-enabled Quantum Computing Networks and Intelligent Resource Allocation," arXiv.org, 13 Jan. 2024. [Online]. Available: arxiv.org/abs/2401.07120.

[12] S. Ganguly, "Implementing Quantum Generative Adversarial Network (qGAN) and QCBM in Finance," arXiv.org, 15 Aug. 2023. [Online]. Available: arxiv.org/abs/2308.08448.

[13] S. Jain, et al., "Comparing Classical and Quantum Generative Learning Models for High-Fidelity Image Synthesis," Technologies, vol. 11, no. 6, Dec. 2023, p. 183. doi: 10.3390/technologies11060183.

[14] S. Kumar, S. Simran and M. Singh"Quantum Intelligence: Merging AI and Quantum Computing for Unprecedented Power," IEEE Conference Publication, IEEE Xplore, 22 Mar. 2024.

[15] M. Rath and H. Date, "Quantum Data Encoding: A Comparative Analysis of Classical-to-Quantum Mapping Techniques and Their Impact on Machine Learning Accuracy," EPJ Quantum Technology, vol. 11, no. 1, Oct. 2024. doi: 10.1140/epjqt/s40507-024-00285-3.

[16] X. Gao, Z. Zhang, and L. Duan, "An Efficient Quantum Algorithm for Generative Machine Learning," arXiv (Cornell University), Jan. 2017. doi: 10.48550/arxiv.1711.02038.

[17] C. Gyurik and V. Dunjko, "Exponential Separations Between Classical and Quantum Learners," arXiv (Cornell University), Jan. 2023. doi: 10.48550/arxiv.2306.16028.

[18] X.-S. Gao, Z. Zhang, and L. Duan, "A Quantum Machine Learning Algorithm Based on Generative Models," Science Advances, vol. 4, no. 12, Dec. 2018. doi: 10.1126/sciadv.aat9004.

[19] S. Lloyd and C. Weedbrook, "Quantum Generative Adversarial Learning," Physical Review Letters, vol. 121, no. 4, Jul. 2018. doi: 10.1103/physrevlett.121.040502.

[20] H. Situ, Z. He, Y. Wang, L. Li, and S. Zheng, "Quantum Generative Adversarial Network for Generating Discrete Distribution," Information Sciences, vol. 538, p. 193, Jun. 2020. doi: 10.1016/j.ins.2020.05.127.

[21] M. C. Saurabh Pahune, "Several categories of large language models (llms): A short survey," *arXiv*, 2023, doi: arXiv preprint arXiv:2307.10188.

[22] H. S. Saurabh A Pahune, Puneet Matapurkar, Sumeet Mathur, "Generative Adversarial Networks for Improving Detection of Network Intrusions in IoT Environments," *4th Int. Conf. Distrib. Comput. Electr. Circuits Electron.*, pp. 1–6, 2025.

[23] S. Pandya, "Comparative Analysis of Large Language Models and Traditional Methods for Sentiment Analysis of Tweets dataset for text classification," *Int. J. Innov. Sci. Res. Technol.*, vol. 9, no. 12, 2024.

[24] R. Q. Majumder, “Machine Learning for Predictive Analytics: Trends and Future Directions,” *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 04, pp. 3557–3564, 2025.

[25] G. P. Vinay Singh, “Enhancing Tax Technology with AI/ML: Monitoring ERP Transactions for Real-Time Compliance and Efficiency,” *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 13, no. V, 2025.

[26] M. Schuld, I. Sinayskiy, and F. Petruccione, "An Introduction to Quantum Machine Learning," Contemporary Physics, vol. 56, no. 2, p. 172, Oct. 2014. doi: 10.1080/00107514.2014.964942.

[27] [23] M. Y. Niu, et al., "Entangling Quantum Generative Adversarial Networks," Physical Review Letters, vol. 128, no. 22, Jun. 2022. doi: 10.1103/physrevlett.128.220505.

[28] S. Chakrabarti, Y. Huang, T. Li, S. Feizi, and X. Wu, "Quantum Wasserstein Generative Adversarial Networks," arXiv (Cornell University), Jan. 2019. doi: 10.48550/arxiv.1911.00111.

[29] R. Shu, X. Xu, M. Yung, and W. Cui, "Variational Quantum Circuits Enhanced Generative Adversarial Network," arXiv (Cornell University), Feb. 2024. doi: 10.48550/arxiv.2402.01791.

[30] N. A. Sharma, A. B. M. S. Ali, and M. A. Kabir, "A Review of Sentiment Analysis Tasks, Applications, and Deep Learning Techniques," Jul. 2024.

