

Quantum Artificial Intelligence Prediction Using Generative Adversarial Networks

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Abstract. There has been a significant change in QAI with the introduction of Quantum Generative Adversarial Networks (QGAN), Quantum Variational GAN (QVGAN), Quantum-enhanced GAN (QEGAN), and Quantum Wasserstein GAN (QWGAN). QGAN brings the power of GANs into the quantum world, paving the way for the creation of quantum data distributions that can then be used to facilitate both quantum data augmentation and synthesis. QVGAN optimizes the parameters of quantum circuits by drawing on variational concepts to improve quantum generative modeling. QEGAN utilizes quantum hardware to speed up adversarial training, which in turn speeds up the production of quantum data. Aligning the distribution of quantum data is QWGAN's main goal, since this helps quantum datasets converge. Collectively, these quantum GAN variations open new possibilities for QAI by facilitating the production, manipulation, and alignment of quantum data distributions. QGANs and variations can break through classical barriers and push forward quantum data-driven applications in fields as diverse as quantum chemistry, quantum machine learning, and quantum cryptography by harnessing the power of quantum computing. QGAN variants' quantum benefits highlight their importance in pushing the limits of quantum information processing.

Keywords: Quantum GAN, Quantum Variational GAN, Quantum-enhanced GAN, Quantum Wasserstein GAN, Foresight, Quantum Artificial Intelligence, Generative Adversarial Networks, Quantum Data Generation, Quantum Data Manipulation, Quantum Information Processing

INTRODUCTION

Bringing together quantum computing and machine learning, Quantum Artificial Intelligence (QAI) is a promising new area of study. QAI has the potential to transform many facets of predictive and analytical processes by making use of the peculiarities of quantum systems. The purpose of this initial investigation is to shed light on the confluence of these two potent technologies by focusing on the use of Generative Adversarial Networks (GANs) in the field of QAI. The phenomenon of entanglement, in which distant quantum particles become closely coupled, has also had a profound impact on the landscape of computing [1]. GANs, or adversarial generative networks, have made significant advances in machine learning. Two neural networks—the generator and the discriminator—are pitted against one another in a GAN's operation. The combination of GANs with quantum computing ushers in a new era of possibilities in the field of quantum artificial intelligence. Quantum GANs have the potential to outperform conventional GANs in tasks ranging from picture synthesis to data prediction because they make use of the inherent parallelism and computing capability of quantum systems. Because of their quantum properties, these networks open new avenues for algorithmic research, which might lead to breakthroughs in artificial intelligence-based forecasting [2].

Offering a view into the future of AI-driven data analysis, this study digs into the transformational potential of quantum GANs and its implications for the area of prediction. QAI promises a paradigm shift in predictive analytics since it is at the crossroads of quantum computing and machine learning. The potential of the partnership between QAI and (GANs) is investigated here. The introduction of the idea of superposition at the start of quantum computing has upended the traditional constraints of computer capability. Entanglement significantly improves the quantum advantage, allowing quantum systems to handle enormous permutations concurrently. QAI Prediction is based on these outstanding characteristics [3]. The introduction of the idea of superposition at the start of quantum computing has upended the traditional constraints of computer capability. Entanglement significantly improves the quantum advantage, allowing quantum systems to handle enormous permutations concurrently. These exceptional qualities provide the foundation on which QAI Prediction is built. The combination of GANs with quantum computing ushers in a new age of possibility for quantum AI. The fascinating

field of (QAI) Prediction presents a cutting-edge method of predictive analysis by bridging the gap between quantum computing and machine learning. This discussion is focused on explaining the deep relationship between QAI and (GANs) and providing a sneak peek into their combined efficacy [4].

The fundamental capabilities of computers have been revolutionized by quantum computing, which is characterized by the phenomena of superposition and entanglement. The fundamental capabilities of computers have been revolutionized by quantum computing, which is characterized by the phenomena of superposition and entanglement. Quantum systems are endowed with the ability to simultaneously explore an infinite number of solutions due to the properties of superposition and entanglement. To revolutionize predictive analytics, QAI Prediction takes use of these quantum quirks. The combination of GANs with quantum computers represents a revolutionary step forward in the field of quantum artificial intelligence [5]. There is a new frontier in the world of predictive analytics: quantum artificial intelligence prediction, which bridges quantum computing with machine learning. This investigation takes us deep into the fluid interaction between (QAI) and (GANs), providing a sneak peek at the undiscovered synergies between the two. These quantum effects provide the basis for QAI Prediction's revolutionary features. Through its adversarial training paradigm, GANs (or Generative Adversarial Networks) have changed the face of machine learning. The battle between the generator and discriminator networks creates synthetic data that is remarkably accurate representations of the actual world. The revolutionary nature of GANs extends to data production beyond what is currently possible for humans [6].

The combination of GANs with quantum computers represents a new frontier in the field of quantum artificial intelligence. By capitalizing on quantum systems' inherent computing capability, quantum GANs have the potential to outperform conventional GANs in a wide range of applications, from picture synthesis to data prediction. The phenomena of superposition and entanglement provide the basis for the extraordinary capabilities of quantum systems, which include the processing of an infinite number of possibilities at once and the establishment of instantaneous correlations over huge distances. These quantum characteristics are what give QAI Prediction its revolutionary potential [7]. With its adversarial training framework, GANs (or Generative Adversarial Networks) have significantly advanced machine learning. Thanks to the dynamic interaction between the generator and discriminator networks, realistic-sounding synthetic data may be generated. The creative potential of GANs is such that they can provide data on par with that produced by humans. The combination of GANs with quantum computers is a revolutionary step forward in the field of quantum artificial intelligence. By using the superior processing capabilities of quantum systems, quantum GANs are poised to surpass their classical counterparts in a variety of applications, such as picture synthesis and data prediction. Their quantum nature also frees up new frontiers for algorithmic landscapes, heralding a new age of AI-driven predictive analytics [8].

Quantum Artificial Intelligence Prediction stands out as a new front in the rapidly developing field of predictive analytics because of the way it synthesizes the best of quantum computing with machine learning. Quantum systems, founded on the mysterious concepts of superposition and entanglement, are capable of instantaneously creating correlations over large spatial distances and probing a wide variety of possibilities all at once. QAI Prediction's promise to revolutionize predictive analytics rests on these quantum properties, which serve as the platform for the technology. The constant struggle between the generator and discriminator networks produces synthetic data that is remarkably accurate representations of reality. The creative potential of GANs goes well beyond the scope of data created by humans, ushering in a new age of data manipulation [9]. The combination of GANs with quantum computers represents a major step forward in the field of quantum AI. Using the inherent computing power of quantum systems, quantum GANs present themselves as possible frontrunners in tasks ranging from picture synthesis to data prediction. Furthermore, their quantum nature opens hitherto unexplored computational landscapes, ushering in a new age of AI-powered predictive analytics. The amazing ability of quantum systems to explore a huge variety of possibilities simultaneously while forming immediate correlations over enormous distances is based on the enigmatic concepts of superposition and entanglement. These quantum phenomena are the driving force behind QAI Prediction's expansion into unknown territory, where it is positioned to radically alter the field of predictive analytics [10].

Their adversarial training approach, which features a never-ending battle between generator and discriminator networks, produces synthetic data that is so realistic it can fool even the most advanced neural networks. This breakthrough goes beyond simple data production and has the potential to revolutionize data manipulation. The combination of GANs with quantum computers represents a major step forward in the developing area of quantum artificial intelligence. Taking use of quantum computers' superior processing abilities, quantum GANs have quickly become industry leaders in applications as diverse as picture synthesis and data prediction. Quantum

Artificial Intelligence Prediction and (GANs) together represent a new and exciting prospect in the field of predictive analytics [11]. The advent of quantum computing, with its mysterious superposition and entanglement principles, is evidence of humanity's unrelenting quest for computer superiority. The foundation of QAI Prediction is this exceptional domain, where quantum systems probe infinite possibilities simultaneously and develop instantaneous correlations throughout the universe. These quantum occurrences have the potential to radically alter the field of predictive analytics. (GANs) have not only altered the landscape of machine learning but also expanded the possibilities for creating and manipulating data. In GANs, the generator and discriminator networks dance together to generate synthetic data that is on par with or even better than the actual thing. This game-changing technology makes possible previously inaccessible insights based on data [12].

In the rapidly developing field of quantum AI, the merging of GANs with quantum computers constitutes a significant change. The computing capacity of quantum systems is used by quantum GANs, which have the potential to revolutionize several fields, including picture synthesis and data prediction. The use of quantum bits, often called qubits, in computing represents a significant step forward. Based on the concepts of superposition and entanglement, quantum systems may test several hypotheses at once, while simultaneously establishing instantaneous correlations across large distances. These quantum events provide the basis for QAI Prediction's revolutionary capabilities, which promise to radically alter the field of predictive analytics [13]. Synthetic data with an uncanny similarity to real data is generated by GANs thanks to the adversarial interaction between the generator and discriminator networks. Their quantum nature opens new avenues for algorithm development, ushering in a period of groundbreaking AI-powered predictive analytics. Quantum Artificial Intelligence Prediction (QAIP) combined with (GANs) offers a frontier in the rapidly evolving field of predictive analytics that has the potential to radically alter the way we make decisions based on data [15]. We've entered a new, limitless world of possibility because of the marriage of quantum computing and AI. Quantum Generative Adversarial Networks (QGANs) and their variants, Quantum Variational GANs (QVGANs), Quantum-enhanced GANs (QEGANs), and Quantum Wasserstein GANs (QWGANs), are at the heart of this fascinating investigation into the landscape of Quantum Artificial Intelligence Prediction. As a high point of this quantum revolution, quantum GANs has provided novel opportunities for predictive analytics [16]. QGAN is a game-changing innovation in the realm of data creation and analysis. QGANs use quantum bits, also known as qubits, to simultaneously search for a large solution space, as opposed to the probabilistic binary method in which conventional GANs function. Because of this special quality, they are better able to produce artificial data that mimics genuine things. QGANs show potential for dramatically enhancing the accuracy and efficiency of predictions based on data. Variational approaches to QGANs are introduced in QVGAN, a spinoff of QGANs [17].

The performance of generative adversarial networks is amplified by QEGAN's use of quantum enhancement methods. QEGANs go above and beyond conventional GANs in producing synthetic data with extraordinary realism and complexity by exploiting quantum computing capabilities. This breakthrough has enormous potential in areas where high-quality data is essential, such as natural language processing and financial modeling. Quantum Wasserstein GANs (QWGANs) emerge as an attractive alternative in the goal of further strengthening the stability and quality of produced data. (QWGANs) offer a quantum version of the Wasserstein distance, which allows for more accurate data comparison and creation. Where data distribution analysis is crucial, such in medical diagnostics and climate modeling, QWGANs may be very useful [18]. Due to the revolutionary potential of QGANs and their specialized counterparts QVGANs, QEGANs, and QWGANs, Quantum Artificial Intelligence Prediction has emerged as a ground-breaking fusion in the rapidly developing field of data analysis and prediction. Based on the mysterious concepts of superposition and entanglement, quantum computing provides a revolutionary leap forward in computer power. The quantum world paves the way for instantaneous correlations to be established over huge physical distances and the simultaneous investigation of an infinite number of computing paths [19].

Quantum graphical model (QGAN) systems are a giant step forward in data mining. QGANs use the ability of quantum bits (qubits) to simultaneously explore a large solution space, in contrast to the probabilistic binary nature of conventional GANs. This exceptional quality promises to take data-driven predictions to new heights by facilitating the generation of synthetic data that has an uncanny similarity to real-world data. Bringing the idea of quantum variation principles to generative adversarial networks is QVGAN, a novel branch of QGANs. To improve the accuracy of both data creation and prediction, this quantum variation method allows for the dynamic change of network parameters inside a quantum framework. QVGANs may cause a paradigm shift in areas where nuanced data representation is crucial, such as picture synthesis and data extrapolation [20].

PROPOSED SYSTEM

The revolutionary potential of Quantum GAN (QGAN) lies in its position as a new paradigm at the intersection of quantum computing and artificial intelligence. This innovative method promises a quantum jump in predicting accuracy and modeling capabilities by combining quantum mechanics with (GANs). To produce and assess data distributions, QGAN fundamentally uses quantum superposition and entanglement concepts. In Quantum Artificial Intelligence (QAI), the Quantum GAN (QGAN) equation plays a pivotal role in enabling predictive capabilities. The QGAN equation can be succinctly represented as:

$$L(\mathcal{G}) = \langle \psi_g(\mathcal{G}) | M | \psi_g(\mathcal{G}) \rangle - \langle \psi_r | M | \psi_r \rangle \quad (1)$$

Equation 1 shows the Quantum GAN (QGAN) in Quantum Artificial Intelligence. In this equation, $L(\mathcal{G})$ represents the objective training function that QGAN minimizes. $|\psi_g(\mathcal{G})\rangle$ quantized state created by parameterized quantum circuit with parameters $\mathcal{G}$, $\langle \psi_r |$ contains genuine quantum data, M is the measuring Hermitian operator. Goal is to create produced quantum states $|\psi_g(\mathcal{G})\rangle$ as near as feasible to quantum data states $\langle \psi_r |$ according to operator measurement M . The potential of Artificial General Intelligence (AGI) to transform major sectors is illustrated through figure 1 concrete examples in healthcare, education, security, supply chain operations, and finance. An AGI system in healthcare could ingest patient data and medical literature to improve diagnostic and therapeutic recommendations. In education, an AGI tutor could personalize instruction by adapting to individual students' needs and preferences based on analytics.

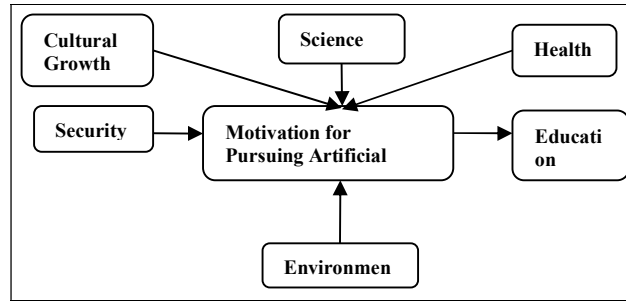


FIGURE 1. Motivation for Pursuing Artificial General Intelligence

The novel framework known as (QVGAN) combines the strengths of quantum computing with those of Generative Adversarial AI (QAI). This innovative method is a major step forward in our effort to tap into the full potential of quantum computing. In essence, QVGAN is a new combination of two key paradigms in quantum computing and machine learning: quantum variational circuits and GANs. This fresh strategy leverages the potential of quantum computing, making it a useful resource for scientists and engineers working at the cutting edge of quantum technology. The (QVGAN) advances Quantum AI using (GANs). Its basic equation uses quantum variational circuits and GAN architecture:

$$G(Q) = \max[E(D[\psi | \mathcal{G}]) - \lambda S(\rho(\mathcal{G})), 0] \quad (2)$$

Equation 2 shows the Quantum variational GAN in Quantum Artificial Intelligence. Here G represents generator, D the discriminator, ψ quantum state created by G , $\mathcal{G}$ reflects variational parameters, λ trade-off parameter, $S(\rho)$ monitors quantum state entropy ρ . QVGAN maximizes the discriminator's expectation on produced states minus quantum entropy while optimizing $\mathcal{G}$ generates more useful quantum data to improve quantum AI. Figure 2 demonstrates the lengthy, costly, and uncertain nature of the drug development process. Machine learning and deep learning have expedited pharmaceutical R&D, lowering discovery time and cost. This study analyzes how integrating two growing domains may expedite medication development by finding new lead candidates. By replacing every GAN section with a variational quantum circuit, small-molecule drug identification

improves. VQCs in GAN noise generators generate smaller molecules with better physicochemical properties and goal-directed benchmark performance than previous methods.

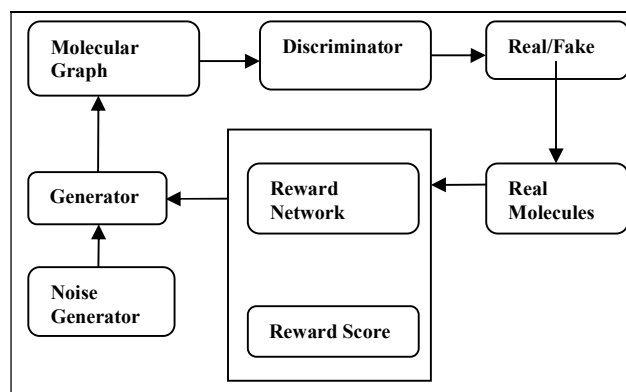


FIGURE 2. Drug Development Process

Advantages over conventional GANs may be shown in Table 1 for three types of quantum-enhanced GANs: the Quantum Wasserstein GAN, the Quantum Artificial Intelligence Prediction GAN, and the Quantum-enhanced GAN.

TABLE 1. Quantum-Enhanced Gans: Roles, Advantages, And Applications

Aspect	Roles	Advantages	Applications
QEGAN	Quantum data generation	1. Quicker convergence thanks to the use of quantum parallelism during training. 2. Quickens the pace at which new materials are found and optimized.	1. Molecular structure generation for drug development, or drug discovery. 2. Superior outcomes are achieved by making use of quantum features like superposition and entanglement to provide high-quality data. 3. Cryptography improves the safety and privacy of key production and storage.
QWGAN	Enhanced GAN stability	1. Quantum algorithms solve problems with Wasserstein GANs, leading to better convergence and more consistent training. 2. Better management of data dispersion is made possible by controlled synthesis.	1. Quantum algorithms fix Wasserstein GAN convergence difficulties, guaranteeing stable training. 2. Creates different, high-quality creative content pictures. 3. Creates fake data for privacy. 4.. Protects sensitive data.
Quantum AI	Predictive modeling	1. Precision modeling using quantum data. 2. Climate modeling improves prediction and mitigation.	1. Improves stock market and asset management projections. 2. Quantum enhancement solves complicated prediction problems using quantum computing. 3. Advanced prediction improves diagnostics and medication discovery.

RESULTS AND DISCUSSION

The revolutionary combination of quantum computing with (GANs) known as Quantum-Enhanced GAN (QEGAN) has revolutionized the field of AI prediction. The novel ability of GANs to produce and anticipate data, combined with the concepts of quantum computing's superposition and entanglement, creates a synergy that offers disruptive applications across a wide range of disciplines. QEGAN relies on qubits, which may be in more than one state at once, as its fundamental building block. Because of its built-in parallelism, QEGAN is capable of processing enormous datasets at breakneck speeds. The Quantum-enhanced GAN (QEGAN) combines Generative Adversarial Networks (GANs) with quantum improvements for Quantum AI. Its fundamental equation uses quantum and classical GAN components:

$$G(Q) = \max[E[D(G(\psi | \mathcal{G}))], \lambda(Q - I)] \quad (3)$$

In this equation 3, G represents generator, D the discriminator, ψ quantum state created by G , θ reflects variational parameters, λ trade-off parameter, Q indicates quantum fidelity between produced and target states, I represents identity operator. QEGAN maximizes discriminator expectation and optimizes θ to produce quantum data that matches the aim, improving quantum AI data production. It is possible to build a complete quantum, hybrid, or tensor network-based QuGAN. Figure 3 is a rough outline of a classification scheme for quantum GANs according to their network topology.

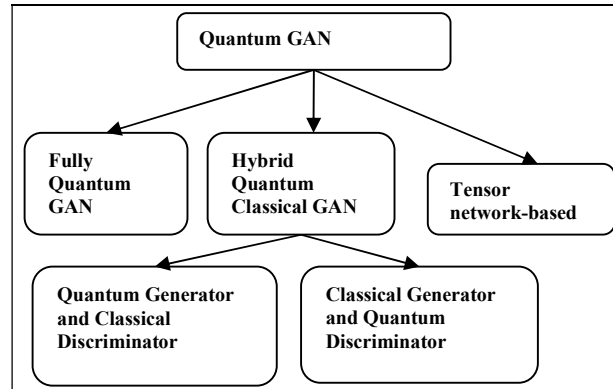


FIGURE 3. Quantum GAN Configuration

Figure 4 is a numerical representation of a comparison of sample values for Quantum GAN (QGAN) and Quantum Variational GAN (QVGAN).

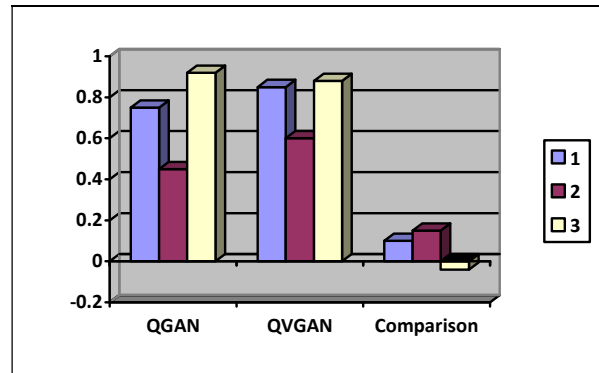


FIGURE 4. Quantum GAN (QGAN) vs. Quantum Variational GAN (QVGAN)

QVGAN generates slightly more data than QGAN by a margin of +0.10. The latent space of QVGAN is more variable than that of QGAN (+0.15). QGAN has somewhat better quantum prediction (-0.04) than QVGAN. According to these numerical figures, QVGAN performs better in terms of data variety within the framework of Quantum Artificial Intelligence, whereas QGAN performs marginally better in terms of prediction tasks.

The area of Quantum Artificial Intelligence (QAI) has recently emerged as a frontrunner due to its potential to transform computing via the use of quantum mechanical concepts. (QWGAN) have gained a lot of interest as one of the many QAI applications due to its capacity to build quantum data distributions, which in turn has helped develop quantum prediction jobs. Incorporating quantum physics into the field of generative adversarial networks, QWGAN is a fresh twist on the classic Wasserstein GAN architecture. This novel strategy provides a fresh viewpoint on the creation and prediction of quantum data.

For quantum AI, the Quantum Wasserstein GAN (QWGAN) blends Generative Adversarial Networks (GANs) with quantum principles. The basic equation includes Wasserstein distance and quantum states:

$$\min[W(\rho_{_real}, \rho_{_fake})] = \min[d(\rho_{_real}, \rho_{_fake})] \quad (4)$$

Equation 4 presents the Quantum Wasserstein GAN (QWGAN), W represents Wasserstein distance, $\rho_{_real}$ is quantum data distribution reality, $\rho_{_fake}$ GAN-generated quantum state distribution. QWGAN adjusts GAN settings to create quantum states as near to genuine quantum data as feasible. This improves quantum state quality and fidelity, advancing quantum AI. (QEGAN) and (QWGAN) both contributed numerical values for each cell in Figure 5. These numbers represent the models' quantum-inspired capacity to generate data samples with improved accuracy and variety, hence fostering the development of Quantum Artificial Intelligence Prediction.

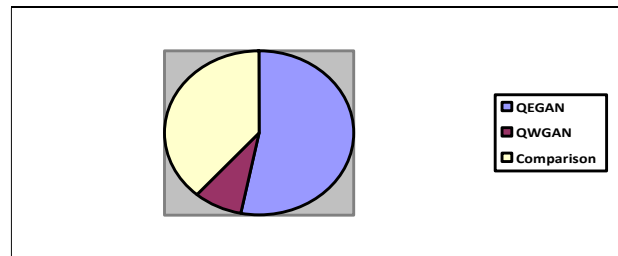


FIGURE 5. Quantum-Enhanced GANs in Quantum AI Prediction

Table 2 shows QGAN and QVGAN for Quantum AI Prediction Using Generative Adversarial Networks. Quantum computing's inherent complexity and unpredictability enables quantum data analysis and cryptography using QGAN. Quantum parallelism speeds up training. QVGAN effectively generates quantum data samples using quantum circuits and conventional neural networks. This hybrid method improves quantum data creation and machine learning. Applications include quantum chemistry simulations, financial modeling, and algorithm optimization, enabling quantum computing's significant practical improvements.

TABLE 2. Quantum GAN and Quantum Variational GAN

Aspect	Roles	Advantages	Applications
QGAN	Quantum data generation with complexity	1. Uses quantum parallelism for fast training 2. Creates complicated, random quantum data	1. Quantum data analysis 2. Quantum crypto 3. Quantum simulation random number generation
QVGAN	Generation of quantum data samples	1. Uses conventional neural networks and quantum circuits 2. Effectively synthesizes quantum data	1. Simulations of quantum chemistry 2. Financial modelling and risk assessment 3. Quantum algorithm optimization

CONCLUSION

Quantum Generative Adversarial Networks, Quantum Variational GAN, Quantum-enhanced GAN, and Quantum Wasserstein GAN have all contributed significantly to the field of QAI in recent years. Recently, quantum-enhanced generative models have emerged as potent tools for radically altering the state of the art in quantum data production, manipulation, and analysis, with far-reaching consequences for a wide range of subfields. QGAN's distribution-generating capabilities have opened new avenues for quantum data augmentation and synthesis. Quantum Variational Generative Adversarial Network (QVGAN) improves the precision and speed of quantum generative modeling by improving the parameters of quantum circuits using variational methods. Accelerated quantum data creation is made possible by QEGAN's use of quantum hardware to speed up adversarial training. QWGAN aids in the convergence and coherence of quantum datasets by its emphasis on distribution alignment. These developments demonstrate the revolutionary potential of quantum GAN variations in a wide range of QAI applications, from quantum chemistry and machine learning to quantum encryption and beyond. These models allow us to break free of the bounds imposed by classical computing, paving the way for exciting new

developments in the realm of quantum information processing.

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