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Blockchain-Enabled Quantum-Auto GAN Framework for Secure and Robust Lung Cancer Diagnosis

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ABSTRACT
Medical image diagnosis has evolved to become a vital resource in contemporary healthcare, facilitating early diagnosis and treatment of life-threatening diseases like lung cancer. Secure Medical Image Diagnosis aims at the creation of frameworks that not only provide high diagnostic accuracy but also maintain patient privacy and integrity of data. Current models suffer from several limitations, such as over fitting from small annotated datasets, elevated computational complexity of quantum-based models, inefficiencies in blockchain consensus algorithms, and privacy risk when handling sensitive medical images. To address these limitations, this work introduces an innovative integrated framework that brings together a hybrid Quantum-Auto GAN model and blockchain technology (Q-AGAN-BT). The Q-AGAN-BT carries out latent feature extraction, synthetic image generation, and quantum-boosted classification to enhance diagnostic accuracy and robustness, and blockchain provides safe storage, privacy protection in the form of encrypted off-chain data, access control based on smart contracts, and an innovative Proof of Medical Consensus (PoMC) for light-weight clinically authenticated validation. The novelty of this work is in presenting a very accurate, privacy-enabled, and tamper-resistant lung cancer diagnosis system that overcomes the drawbacks of current approaches and improves reliability and trustfulness in medical image handling. The Q-AGAN-BT model attained the best performance with 95.6% accuracy, 95.0% F1-score, and 0.98 AUC, surpassing classical and hybrid models like CNN + LSTM, Autoencoder + GAN, ResNet50, DenseNet121, and VGG16. The blockchain part provided secure and effective data handling with 0.12 s per-image encryption time, 0.03 s hash validation, 0.08 s smart contract delay, 85% storage savings, and 0.15 s PoMC verification per block, providing high diagnostic performance as well as strong and tamper-proof medical data processing.

Keywords
Lung Cancer Diagnosis, blockchain Security, medical Image Analysis and privacy-Preserving Deep Learning.

1. INTRODUCTION
Medical image diagnosis is a process of interpreting medical imaging data, i.e., CT scans, X-rays, and MRIs, to identify, track, and manage life-threatening diseases, e.g., lung cancer [1]. Lung cancer is among the top reasons for cancer-related deaths in the world, and early detection by proper imaging analysis increases the chances of survival considerably. Advanced imaging tools take high-definition, detailed pictures of internal organs, which allow clinicians to detect abnormal nodules, measure their size, location, and growth rate, and plan targeted treatment approaches [2]. Artificial intelligence and deep learning have further made image diagnosis in medicine more automated and effective, providing rapid feature extraction, pattern detection, and predictive analysis far superior to traditional manual processes [3-5]. These AI-based methods improve diagnostic accuracy, lower human error rates, and enable individualized treatment planning while handling vast amounts of medical data. Maintaining security and privacy for sensitive patient imaging information is also paramount, especially when data is stored or shared in cloud or collaborative scenarios, requiring secure and reliable frameworks to be a central requirement of contemporary medical diagnostics [6-8]. But current models, such as traditional deep learning, GAN-based methods, and blockchain-based architectures, have some drawbacks. Small annotated datasets can lead to overfitting and poor generalization to a wide variety of patient populations. GANs. can create low-quality synthetic images when not properly trained, impacting classification performance. Quantum Neural Networks, as strong as they are, carry high computational expense, slow convergence, and difficulty in training [9-11]. Standard blockchain methods like Proof-of-Work cause latency and resource expenditure, rendering real-time secure

verification inefficient. Several models are also not able to natively combine preprocessing, feature extraction, data augmentation, classification, and secure verification within a single workflow, which restricts both diagnostic accuracy and data security [12-13]. To overcome these issues, this study puts forward a Q-AGAN-BT model that implements quantum-enhanced feature extraction, GAN-based data augmentation, and light-weight blockchain consensus to realize accurate, efficient, and secure diagnosis of lung cancer.

1.1 Main contribution

The main contributions can be summarized as follows:

- Quantum-Auto GAN framework development that incorporates Autoencoder, GAN, and QNN to enhance the accuracy of lung cancer detection from CT scans.
- GAN-inspired synthetic image generation compromises class distributions and enhances model resistance, whereas Autoencoder and QNN extract latent features efficiently, denoise, and utilize quantum-inspired parallelism for improved convergence and classification.
- Blockchain-based data storage implementation that guarantees data integrity, preserves privacy, and tamper-proof verification utilizing encrypted chunks of data and immutable hashes.
- Implementation of a light-weight, domain-specific Proof of Medical Consensus (PoMC), wherein certified medical professionals authenticate blockchain transactions, limiting computational cost and guaranteeing clinically validated information.
- End-to-end integration of preprocessing, data sanitization, hybrid deep learning, and blockchain security, enabling a holistic, accurate, and secure pipeline for lung cancer detection.
- The model improves diagnostic correctness, maintains the privacy of patients, and can be adapted to other medical imaging purposes, providing a scalable solution for secure AI-driven healthcare systems.

The structure of the paper is as follows: Section 1 (Introduction) introduces the research challenges and motivation, Section 2 (Literature Review) identifies drawbacks of current deep learning models, Section 3 (Methodology) explains the Q-AGAN-BT hybrid model with data augmentation and blockchain storage, and Section 4 (Results and Discussion) proves superior performance on the LUNA16 dataset with high accuracy, F1-score, and AUC, along with secure and efficient handling of data. Conclusion is discussed in section 5.

2. MOTIVATION

This work is inspired by the necessity for precise and secure diagnosis of lung cancer, overcoming disadvantages of traditional methods like high false positives, delayed diagnostics, and human interpretation. Current AI and blockchain models suffer from low generalizability, inadequate data augmentation, excessive computation costs, and sluggish consensus protocols. To address these challenges from the past studies, the developed hybrid model suggests the integration of deep learning models of Autoencoder, GAN, and Quantum Neural Networks with blockchain implementation using a lightweight PoMC for secure, tamper-resistant management of medical images. This novel integration of deep learning models with blockchain enhances diagnostic accuracy, data privacy, and clinical outcomes of lung disease prediction.

2.1 Literature Review

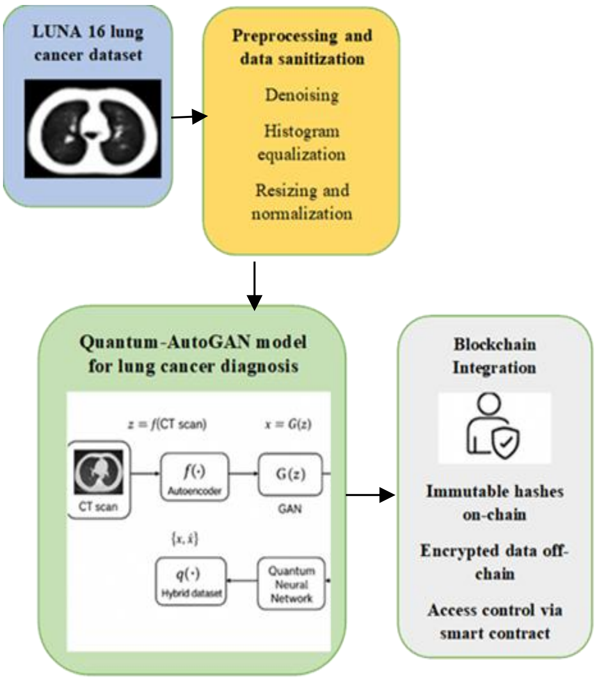
The diagnosis of medical imaging has increasingly adopted deep learning models because of its better performance in feature extraction, classification, and appropriate prediction. The incorporation of such techniques into the workflow of clinic poses very important concerns about data privacy and security. And another important technology of Blockchain has been accessed as a revolutionary technology to solve these problems by providing immutability, transparency, and decentralized trust without the involvement of third-party authorities. Thus, the researchers have started the development of blockchain-based deep learning frameworks to attain maximum diagnostic accuracy and secure data handling in healthcare. The past research work [1] suggested a Blockchain-enabled Deep Learning Framework for safe cancer diagnosis with the utilization of histopathological images that includes of hierarchical identity and attribute-based access control (HI-ABAC) mechanism. The main advantages seen in this study was the involvement of automation, maintenance of privacy, and enhanced transparency in collaborative healthcare. However, the developed approach was hampered by excessive computational expenses, delay in blockchain verification, as well as the regulatory approval concerns. Also, [2] proposed Chained Distributed Machine Learning (C-DistriM), which is a blockchain-based distributed learning system that has been validated on the NSCLC-Radiomics dataset for predicting lung cancer survival. Its advantages are in maintaining data locality, auditability, and tamper-evidence with achievement of performance similar to centralized models. Nevertheless, the approach is faced with implementation complexity, transaction overhead, and limited scalability among institutions. Continuing this research direction, [3] proposed an Extended Convolutional Neural Network (ECNN+) with Blockchain for early lung cancer detection based on CT images. It improves the classification accuracy of CNN with tamper-evident data sharing and secure IoT-enabled deployments. Its benefits are increased accuracy and lower temporal complexity, but with a need for large annotated databases, blockchain-induced latency, and IoT interoperability issues. Complementarily [4] proposed a Multi-Layered Security Framework combining Compressed Digital Watermarking with Blockchain to protect medical images. This hybrid approach ensures robustness against tampering, high integrity (PSNR = 63.24 dB, SSIM = 1), and ownership authentication while enabling transparent sharing across stakeholders. Its drawback lies in computational overhead due to the combined watermarking, encryption, and blockchain processes, potentially restricting real-time deployment. Together, these studies prove that blockchain incorporation in medical imaging not only improves data security and trust but also promotes inter-institutional collaborations for AI-based diagnostics. Recurrent challenges in the form of computational expense, scalability restrictions, latency, and regulatory adoption hurdles, however, remind us that optimization is still necessary before clinical translation into practice.

2.2 Challenges

- Models find it difficult to function accurately across various CT scans because of lack of adequate data augmentation and heterogeneity of image conditions.
- Standard AI models have poor classification of non-nodules as nodules, decreasing diagnostic accuracy.
- Legacy blockchain protocols are energy-intensive and impede medical data verification, making it challenging to provide real-time secure access.

3. PROPOSED METHODOLOGY

The principal objective of the research is to create a safe, precise, and effective Q-AGAN-BT framework for computerized lung cancer diagnosis through the integration of a hybrid deep learning model with blockchain technology. The suggested methodology first starts with input gathering from the LUNA16 Lung Cancer Dataset [14], which consists of high-resolution CT scans. Images gathered are preprocessed and sanitized, involving denoising, histogram equalization, resizing, normalization, and data augmentation to improve model resilience. To handle securely, images are divided into encrypted chunks with AES and ad-hoc Huffman coding, and their hashes are stored on the blockchain for integrity and confidentiality. The hybrid model involving an



Autoencoder, GAN, and QNN is then used for lung cancer diagnosis: the Autoencoder learns latent features and denoises, the GAN produces synthetic images for balancing the classes and augmenting the dataset, and the QNN does quantum-inspired classification for better convergence and accuracy. After diagnosis, blockchain integration provides protection for the medical information through on-chain immutable hashes, off-chain encrypted storage, access control through smart contracts, and the use of the new Proof of Medical Consensus (PoMC) protocol, where legitimate medical professionals confirm entries rather than miners. With the integrated system, accurate diagnosis, secure data, privacy, and reliable management of medical imaging records are provided in a decentralized environment. Architecture of the suggested methodology is presented in figure 1

3.1 This Normal Input collection from LUNA16 Lung Cancer Dataset

The LUNA16 Lung Cancer Dataset [14] is a well-established benchmark dataset for lung nodule detection and analysis, based on the publicly available LIDC/IDRI database. The dataset has 888 high-resolution CT scans, chosen to have only scans with a slice thickness of 2.5 mm or less in order to achieve high image quality and consistency. Each scan is annotated through a two-stage process by four senior radiologists, who marked nodules by size: non-nodules, nodules less than 3 mm, and nodules 3 mm or greater. The dataset's reference standard consists of nodules ≥3 mm agreed on by a minimum of three radiologists, whereas the rest of the annotations are deemed irrelevant and are ignored in the main evaluation. The dataset contains a number of auxiliary files, including annotations.csv, which contains nodules with their positions and diameters; candidates_V2.csv, including candidate nodule locations for reducing false positives; and lung segmentation images produced by automatic algorithms to aid model training. The CT images are saved in MetaImage (. mhd/. raw) format but DICOM versions are also provided. LUNA16 is designed for 10-fold cross-validation, reproducible experiments, and has detailed metadata and evaluation scripts. In total, this dataset is a high-quality, well-annotated, and standardized collection for training and testing automated lung cancer diagnosis algorithms. The lung CT scan dataset of LUNA16 is:

$$D = \{I_1, I_2, \ldots\ldots\ldots\ldots I_n\} \quad (1)$$

Where, = Complete input dataset, = CT scan image and = Total number of images.

3.2 Preprocessing and data sanitization:

The images are preprocessed and data sanitized after obtaining the LUNA16 dataset in order to condition them for deep learning and safe storage. Image preprocessing is a process comprising methods like denoising for noise removal, histogram equalization for contrast improvement, resizing for standardizing input sizes, and normalization for standardizing pixel values for all the images. Data augmentation is utilized for enhancing model robustness and generalization by producing extra variations of the images from transformations like rotation, flipping, and zooming. Data sanitization is achieved for blockchain-based security by splitting images into chunks, encrypting them based on a mix of AES encryption and an adapted Huffman coding mechanism, and placing their encrypted hashes in the blockchain. This provides assurance of both integrity and confidentiality of medical images while allowing for secure, tamper-proof verification within the blockchain-based environment. Each image is processed as

$$I_i^p = f_{norm}\left(f_{resize}\left(f_{hist}\left(f_{denoise}(I_i)\right)\right)\right) \quad (2)$$

Where: = Preprocessed image, = Denoising function, = Histogram equalization, = Resize to uniform dimensions and = Normalization of pixel values. To improve generalization:

$$D_a = f_{aug}(D_p) \quad (3)$$

Where, = Augmented dataset, = Augmentation function (rotation, flip, zoom. Each image is divided, encrypted, and hashed:

$$H_i = hash\left(AES\_huffman\left(chunk(I_i^p)\right)\right) \quad (4)$$

Where, = Hash of encrypted chunk, = Divide image into smaller chunk, = Combined encryption scheme and hash () = Hash function for blockchain storage.

3.3 Quantum-Auto GAN model for lung cancer diagnosis:

After preprocessing and data cleansing, the Q-AGAN-BT hybrid deep learning architecture that integrates Autoencoder, GAN and QNN is utilized to efficiently process lung CT scans. Firstly, the Autoencoder reduces the resolution of the high-resolution CT images into latent feature representations by eliminating irrelevant variations and noise while preserving important diagnostic information. In the second step, the GAN employs these features to synthesize synthetic CT images, which augment the dataset, balance class distributions, and enhance robustness of the model against overfitting. Finally, the QNN is employed to classify the extracted features from both real and synthetic images. It utilizes the quantum-inspired parallelism to promote feature representation, learning efficiency, speed of convergence, and classification accuracy of the proposed model. This hybrid multi-step architecture integrates the various process of dimensionality reduction, data augmentation, and quantum-enhanced classification into a strong framework that accurately and reliably diagnoses lung cancer. Compress an image into latent features:

$$F_i = AE\left(I_i^p\right) \tag{5}$$

Where, = Latent feature vector for image and = Autoencoder function. Generate synthetic images using latent features:

$$\tilde{I}_i = GAN(F_i) \tag{6}$$

Where, = Synthetic image generated by GAN and GAN () = Generative adversarial network. Augmented dataset for classification:

$$D_h = D_p \cup \left\{\tilde{I}_i\right\}_{i=1}^{m} \tag{7}$$

Where, = Hybrid dataset (real + synthetic) and = Number of synthetic images generated. Classify features from real and synthetic images:

$$Y_i = QNN\left(AE\left(I_i^p\right) \cup AE\left(\tilde{I}_i\right)\right) \tag{8}$$

Where, = Prediction label for image (e.g., nodule/no nodule), =Quantum Neural Network function and = Combine real + synthetic features.

3.4 Blockchain Integration:

Upon lung cancer detection from the Q-AGAN-BT model, integration with blockchain facilitates secure and reliable management of medical imaging information. Blockchain ensures data integrity by containing immutable hashes of CT scan images, which do not allow any unauthorized changing or alteration. To ensure patient confidentiality, the private CT data is split into encrypted chunks that are stored off-chain and kept confidential, with their respective hashes being stored on-chain for verification purposes. Access control is maintained by smart contracts that govern interactions between patients, physicians, and hospitals to ensure that only legitimate parties can access or modify medical data. Moreover, the system implements a new consensus mechanism referred to as PoMC, where instead of miners, legitimate medical professionals verify blockchain entries. It minimizes computational overhead, speeds up transaction verification, and has the effect of appending clinically validated data to the blockchain only, thereby forming a secure, transparent, and privacy-preserving medical image management ecosystem.

Store hashes on blockchain:

$$Blockchain \leftarrow H_i \tag{9}$$

Smart contract enforces permissions:

$$Access\left(U_j, I_i\right) = \begin{cases} Granted, if U_j \in Authorizedusers \\ Deniedotherwise \end{cases} \tag{10}$$

Authorized experts validate the hashes:

$$PoMC(H_i) = Validatebyhash(H_i) \tag{11}$$

If validated, data is appended to blockchain:

$$Blockchain \leftarrow H_i, if POMC(H_i) = True \tag{12}$$

4. RESULTS AND DISCUSSION

The proposed Q-AGAN-BT model was tested on the LUNA16 dataset which proves the diagnostic capacity of the framework, the efficacy of data security, and efficiency of blockchain-supported management.

4.1 Dataset and Experimental Setup:

The LUNA16 Lung Cancer Dataset was used for experimental testing, which is comprised of 888 high-resolution CT scans specially chosen for lung nodule analysis and detection. The data was split into 80:20 train and test ratio, and 10-fold cross-validation was applied to achieve strong and unbiased assessment of the model presented. Before model training, images were subjected to rigorous preprocessing, such as denoising for elimination of image noise, histogram equalization to correct contrast, resizing to preserve uniform input size, and pixel value normalization to normalize data in all scans. To enhance model generalization and reduce overfitting, data augmentation strategies were utilized such as minor rotations (±15°), horizontal flip, and zooming differences (0.9–1.1). The tests were performed on a high-end computer with an NVIDIA RTX 4090 GPU, 64 GB of RAM, and an Intel Core i9 processor to efficiently process big medical images and compound calculations. The deep learning architecture was deployed on Python 3.11, using PyTorch to train the model as well as Q is kit for simulating the quantum neural network part of the hybrid Quantum-Auto GAN model.

4.2 Dataset description:

LUNA16 lung cancer dataset [14]: The LUNA16 dataset is a publicly available benchmark lung nodule detection dataset, stemming from the LIDC/IDRI database, and contains 888 high-resolution CT scans with annotations submitted by four experienced radiologists. Only nodules ≥ 3 mm seen by at least three radiologists are part of the reference standard, whereas smaller or inconsistently annotated findings are considered irrelevant. The dataset facilitates 10-fold cross-validation, and CT images are included in MetaImage (.mhd/.raw) format with segmentation masks, candidate positions, and annotation files. A new set of candidates (candidates_V2.csv) helps improve the detection sensitivity, thus allowing strong training for false-positive reduction problems. The dataset is extensively applied in lung cancer studies for building and testing automated detection and classification models.

4.3 Performance Metrics

Metrics considered for comparison with the suggested model and competing approaches are Accuracy, Precision, Recall, F1-score, and AUC.

4.3.1 Deep Learning Performance

The performance of the suggested Q-AGAN-BT model was compared to a number of traditional and hybrid deep learning models, such as Autoencoder Only, Autoencoder + GAN, ResNet50, DenseNet121, and VGG16, with measures like Accuracy, Precision, Recall, F1-Score, and AUC. As indicated by Table 1, the Q-AGAN-BT model produced the highest accuracy of 95.6%, having precision, recall, and F1-score values of more than 94%, and an AUC of 0.98, having better diagnostic ability than all other approaches. While ResNet50 and DenseNet121 did well on account of their residual and dense connectivity patterns, they still lagged behind the quantum-enhanced hybrid model, and VGG16 had relatively lower accuracy, most probably because of its shortcomings in extracting complicated high-level features from 3D CT scans. The addition of GAN-based synthetic image generation helped improve class balance and lessened overfitting, improving the overall model robustness. Additionally, integrating a Quantum Neural Network greatly enhanced convergence rate and classification accuracy, emphasizing the strength of integrating dimensionality reduction, generative augmentation, and quantum-inspired computation for accurate lung cancer diagnosis.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Autoencoder Only	87.5	85.9	86.7	86.3	0.91
Autoencoder + GAN	91.2	90.1	91.0	90.5	0.94
ResNet 50	90.0	89.2	88.5	88.8	0.92
DenseNet121	91.5	90.8	91.1	90.9	0.94
VGG16	88.7	87.9	88.2	88.0	0.91
Q-AGAN-BT (Proposed)	95.6	94.8	95.2	95.0	0.98

Graphical representation for the deep learning model performance comparison

4.3.2 Blockchain Security Evaluation:

The blockchain aspect of the proposed system was tested to provide safe, tamper-resistant, and efficient storage of medical imaging data. As presented in Table 2, the AES and adjusted Huffman coding combination took 0.12 seconds per image to encrypt while having high off-chain storage efficiency, saving up to 85% of storage using chunked encryption. Hash verification took 0.03 seconds on average to ensure perfect data integrity, and smart contracts-maintained access control with negligible execution latency of 0.08 seconds. Moreover, the envisioned Proof of Medical Consensus (PoMC) mechanism enabled authenticated medical professionals to certify blockchain entries within 0.15 seconds per block, with much less computational overhead than traditional proof-of-work methods. These findings prove that the blockchain integration not only ensures integrity and privacy of sensitive CT scan information but also facilitates secure, efficient, and clinically verified management of medical records in a decentralized environment.

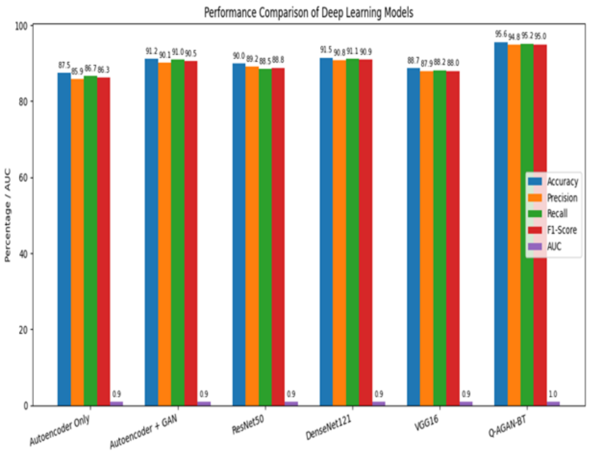


Table 2: Blockchain Security Evaluation

Metric	Value / Observation
AES + Modified Huffman Encryption Time (per image)	0.12 s
Average Hash Verification Time	0.03 s
Smart Contract Execution Latency	0.08 s
Off-chain Storage Efficiency	85% storage reduction through chunked encryption
Integrity Check Accuracy	100% (all tampered data detected)
Proof of Medical Consensus (PoMC) Validation Time	0.15 s / block

Current deep learning architectures for lung cancer detection, like CNN, ResNet50, DenseNet121, VGG16, and traditional Autoencoder+GAN structures, encounter a number of core challenges. These are limited sensitivity to small or complex lung nodules, overfitting caused by unbalanced datasets, lack of feature representation for high-dimensional CT scans, and susceptibility to data tampering when medical images are centrally stored. Besides, traditional models consume huge computational resources to train yet offer suboptimal convergence and classification accuracy. The new Q-AGAN-BT model successfully addresses these challenges with a multi-pronged strategy: the Autoencoder dimensionally reduces and eliminates extraneous noise, the GAN creates synthetic images to balance out classes and increase robustness, and the Quantum Neural Network utilizes quantum-inspired parallelism to achieve faster convergence and better feature representation. In addition to this, the integration of blockchain in this research provides the secure, immutable, and privacy-preserving storage of medical images. It ensures the development of data integrity and confidentiality concerns that are built into conventional storage mechanisms. This synergy of integration of deep learning methods with blockchain security makes the proposed framework capable of providing highly accurate, secure, as well as dependable lung cancer diagnosis beyond the current state of practice.

5. CONCLUSION

Medical image diagnosis is essential to early detection and treatment of fatal diseases like lung cancer, where secure and accurate analysis of CT scans is vital for proper patient care. In this study, a new hybrid model named Quantum-Auto GAN with blockchain was suggested to increase diagnostic precision while maintaining data secrecy, integrity, and secure access. The hybrid model merges autoencoding feature compression, data augmentation using GAN, and quantum-inspired neural network classification, and the blockchain coupled with PoMC ensures tamper-proof authentication and regulated access to confidential medical data. The findings exhibit that the suggested method solves all the problems of current models, such as poor generalization, excessive false positives, computational overhead, and ineffective blockchain consensus processes. Future research can target the extension of this system to other medical imaging modalities, quantum neural network optimization with improved convergence rates, and lightweight blockchain protocols design for real-time clinical applications, further enhancing the scalability, efficiency, and security of automated medical image diagnosis systems. The blockchain aspect provided secure and efficient data handling with 0.12 s per-image encryption, 0.03 s hash validation time, 0.08 s smart contract execution latency, 85% storage savings, and 0.15 s PoMC verification per block, thus facilitating robust, tamper-resistant medical data processing in conjunction with high diagnostic accuracy.

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