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# A Hybrid Quantum Computing and Artificial Intelligence Model for Secure Medical Image Classification and Cancer Prediction

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## Abstract

The process of medical image analysis to find early signs of cancer in patients has gained a lot of importance in enhancing diagnostic accuracy and survival rates of patients. Traditional medical image classification systems based on artificial intelligence also include drawbacks concerning the computational complexity, the sensitive aspects of the data security, and lesser prediction accuracy when working with large datasets in healthcare. Moreover, a key challenge in intelligent healthcare settings is the safe management of sensitive medical images. In solving these problems, this study offers a quantum computing and artificial intelligence system hybrid to be used in the secure medical image classification and cancer prediction. The proposed model combines quantum-enhanced computational learning as well as deep artificial intelligence methods to achieve better classification accuracy, fast feature optimization, and performance in predictions. A safe medical image processing software that uses encryption and privacy-conscious algorithms is followed to safeguard confidential healthcare data in data transfer and analysis. The framework utilizes advanced preprocessing, feature extraction, and hybrid quantum-AI classification approaches in order to identify tumors effectively and predict cancer. Benchmark medical imaging datasets of MRI, CT, and cancer histopathological images were used to evaluate the experiment experimentally. The classification and prediction metrics such as Accuracy, Precision, Recall, Specificity, F1-Score, AUC-ROC, PSNR, and SSIM were used to perform performance assessment. Experimentation has shown that the hybrid framework had a higher classification accuracy, high cancer prediction reliability, high image security, and low computational latency in comparison to the traditional deep learning methods. The suggested model has a huge potential of secure, intelligent and next generation healthcare diagnostic application.

*Keywords: Quantum Computing, Artificial Intelligence, Medical Image Classification, Cancer Prediction, Deep Learning, Secure Healthcare Systems, Hybrid Computing, Precision Medicine*



## 1. Introduction

Early diagnosis of cancer is critical in enhancing the survival of patients, reducing their disease progression, and improving a successful clinical treatment plan. Medical imaging systems like magnetic resonance imaging (MRI), computed tomography (CT), histopathology and X-ray imaging have become essential instruments in the diagnosis of different types of cancer. Nonetheless, the speedy expansion of medical imaging information has made the manual diagnosis process more complicated and established a high need in automated smart systems. Techniques of artificial intelligence (AI) and deep learning have considerably advanced the medical image analysis as they allow automatic detection of tumors, classification of tissues, and predictive diagnosis with a high level of accuracy (Litjens et al., 2017). Healthcare systems powered by AI have already shown a considerable potential in helping clinicians by providing efficient image interpretation and decision-making algorithms (Rajkomar et al., 2019). Also, by combining multimodal machine learning methods, the ability of AI systems to work with more complex healthcare data and to be more predictive has also increased (Baltrušaitis et al., 2018). Current innovations in AI-based radiotherapy and clinical decision support systems have reinforced intelligent healthcare technologies in precision medicine as well (Siddique and Chow, 2020; Prinzi, 2023).

Although the traditional AI-driven medical image classification networks have been successful, various technical constraints still influence them in larger-scale healthcare setups. The computational resources, the data processing capabilities of high dimension and the time needed to effectively optimize the model are usually very high in deep learning frameworks. The implementation of AI on large scales has increased with the use of TensorFlow and other machine learning platforms, but computational complexity and scalability issues are still major concerns when it comes to healthcare analytics (Abadi et al., 2016). Moreover, Data asymmetry in medical data can lead to a decrease in the reconstruction of cancer, which will lead to unbiased classification and sensitivity to diagnosis (Brownlee, 2020). Current AI models also have the problem of failure to comprehensively detect complex tumor structures due to differences in image quality, noise as well as irregular clinical information. Medical decision making contexts have very strict predictive systems which must be able to preserve both computational and diagnostic accuracy in the face of varied medical circumstances (Schwartz, 2011). This has led to increased requirements of sophisticated computing models that are able to overcome such drawbacks by the use of optimized learning models and smart data processing approaches.

Lately, the advancements in quantum computing have presented an encouraging way of enhancing machine learning functionality in healthcare application. Quantum computing provides greater computational parallelism, faster optimization, and effective work with multidimensional data than traditional methods of classical computing. The development of hybrid quantum-classical learning models has become a powerful solution to solving predictive analytics and challenging classification tasks in medical image processing (Ivanova et al., 2024). Cancer prediction systems using quantum machine learning networks are capable of optimizing the feature extraction process, increasing classification accuracy, and decreasing the computational latency (Ur Rasool et al., 2023). Also, quantum gate interactions and quantum neural network designs can offer advanced learning models that can be applied to next-generation intelligent healthcare applications (Mummaneni et al., 2022). Quantum computing plus AI technologies integration is thus a major opportunity to create high-performance cancer prediction systems that can process large-scale medical imaging data more efficiently in a manner that is more effective.

The other essential issue with intelligent healthcare systems is how to securely handle sensitive medical information when storing, transmitting, and performing diagnostic analysis. Healthcare facilities deal with sensitive patient data that is most likely to be targeted by cyber attacks, unauthorized access, and privacy violation. Current AI-based healthcare solutions often do not provide a well-established security architecture that would allow providing security guarantees to the medical image processing and privacy protection. Safety of diagnostic frameworks thus play a critical role in ensuring patient confidentiality as well as supporting reliable healthcare analytics. To address these issues, this study suggests a hybrid quantum computing and artificial intelligence system to identify and classify medical images and determine cancer. To enhance the accuracy of classification, cancer prediction performance, computational efficiency, and the security of medical images, the proposed framework combines quantum-enhanced learning forms, deep AI-based classification algorithms, and secure med medical image processing schemes. A thorough analysis of the comparative performances in the framework through various evaluation values such as Accuracy, Precision, Recall, Specificity, F1-Score, AUC-ROC, PSNR, and SSIM are also done in the study to prove the efficacy of the suggested hybrid framework.

## 2. Literature Review

Medical image analysis has been undergoing rapid changes with the introduction of artificial intelligence (AI) into the field to enhance disease diagnosis automation and accuracy in the current medical systems. The convolutional neural networks (CNNs) and other deep-learning models have proved to be highly effective in medical image classification, tumor detection, and extraction of features in complex imaging data set. By comparing medical images with conventional methods of diagnosing abnormal tissues, CNN-based architectures are capable of detecting the abnormal pattern and classify medical images with greater accuracy than traditional methods of diagnosing abnormal tissue (Litjens et al., 2017). The transfer learning and deep neural network models have also increased the performance of healthcare imaging systems by allowing them to learn effectively using pre-trained large scale datasets. Medical imaging AI uses have been effectively applied to radiotherapy, cancer diagnosis, and intelligent clinical decision support systems (Siddique & Chow, 2020). Moreover, multimodal machine learning methods have enhanced combination of heterogeneous sources of healthcare data, thus facilitating more precise and situational diagnostic forecasts (Baltrušaitis et al., 2018). Deep learning-based image health applications have been efficiently implemented with large-scale machine learning frameworks like TensorFlow (Abadi et al., 2016).

The emergence of machine learning and AI technologies has significantly improved the cancer prediction systems. Conventional machine learning frameworks such as support vector machines (SVM), decision trees, random forests, and k-nearest neighbor algorithms have been extensively used in the diagnosis and classification of tumors to diagnose cancer. Despite moderate predictive accuracy, these approaches could not tend to handle high-dimensional imaging and high-dimensional feature representation. Cancer prediction models based on AI have enhanced the ability to classify cancer through automatic learning of useful features as well as adaptive optimization (Rajkomar et al., 2019). Deep learning systems are able to handle imaging data on a large scale and enhance the reliability of diagnosis in the detection of the malignant and benign tumor patterns. Nonetheless, skewed healthcare datasets continue to be a critical issue of cancer prediction due to the possibility of decreased sensitivity of classifications and false-negative outcomes (Brownlee, 2020). Additionally, the current AI-based cancer prediction systems are often characterized by computational complexity, overfitting, and the low scalability of the systems, working with multidimensional healthcare data. These restrictions suggest there is a need to have more sophisticated computational intelligence models that can enhance the accuracy and the efficiency of predictions.

News in the field of quantum computing has brought a ray of hope to improving the machine learning algorithm in healthcare systems. Quantum machine learning interprets quantum principles of computations and artificial intelligence to optimize, extract features, and process information much faster. It has been shown that hybrid quantum-classical models outperform classical machine learning models when solving complex healthcare analytics tasks (Ivanova et al., 2024). Quantum neural networks and quantum-enhanced feature mapping systems can offer effective learning of high-dimensional medical image processing and predictive healthcare systems (Ur Rasool et al., 2023). Also, quantum gate models and qubit-based models have demonstrated the possibility of enhancing computation speed and optimization in smart healthcare (Mummaneni et al., 2022). Even with these developments, the real world application of quantum computing in medical image classification is still minimal due to the hardware constraints, model instability, and a lack of integration with secure healthcare processing framework. Existing applications mostly come down to either AI-based prediction or quantum computational optimization on its own, without considering overall healthcare security needs.

The need of securing medical data processing has taken center stage in the contemporary intelligent healthcare setting since in most cases healthcare systems are handling delicate patient data prone to cyber attacks and unauthorized personalities. Encryption of medical images, privacy-conscious machine learning, and frameworks that ensure optimal security of healthcare communication have thus been of growing research interest. Elucidable and transparent AI systems have likewise been presented to enhance dependability and confidence in the automated clinical decision-making procedures (Prinzi, 2023). Nonetheless, most of the current healthcare AI systems offer a minimal security control and are inadequate in securing confidential medical imaging information storage and transmissions. Also, existing medical image classification algorithms can frequently not find a compromise between classification accuracy, computational optimization, and data security in one framework. According to the review of literature, there is a considerable research gap that needs to be addressed in the development of integrated hybrid systems that integrate quantum computing, artificial intelligence, and secure medical image processing to help predict cancer in a cost-effective manner. The majority of the past research emphasize individual computational methods instead of larger frameworks that could guarantee great classification performance, computational effectiveness, privacy protection, and secure healthcare analytics at the same time. Thus, the current study suggests a combination of quantum computing and artificial intelligence to perform safe medical image classification and cancer forecasting to overcome these current constraints and enhance intelligent healthcare systems in the future.

## 3. Proposed Hybrid Quantum-AI Framework

### *3.1 System Architecture*

The suggested hybrid quantum computing and artificial intelligence system is meant to offer safe and effective medical image classification and cancer prediction by combining progressive deep-learning and quantum-enhanced calculation systems. The entire architecture comprises of several interdependent layers such as medical image acquisition, preprocessing, deep feature extraction, quantum feature mapping, hybrid classification, secure image processing and cancer prediction modules. First, medical images acquired at MRI, CT, histopathology, and X-ray data are transferred into the preprocessing layer where image normalization, image enhancement and segmentation tasks are carried out to enhance the quality of the images and minimize the unrelated noise. These features are then fed into a hybrid quantum-AI learning architecture based on incorporating deep neural networks, together with quantum computational optimization methods, to enhance both the accuracy of classification and computational efficiency. The framework also includes safe encryption and privacy-saving solutions to enhance the safety of sensitive healthcare information when transmitting and processing images. Lastly, the cancer prediction module categorizes cancer images as benign, malignant or multi-class cancer images based on optimized hybrid learning strategies.The complete workflow and interaction between the computational layers are illustrated in Figure 1, which demonstrates the systematic flow of medical image processing, secure data handling, quantum feature optimization, and cancer prediction

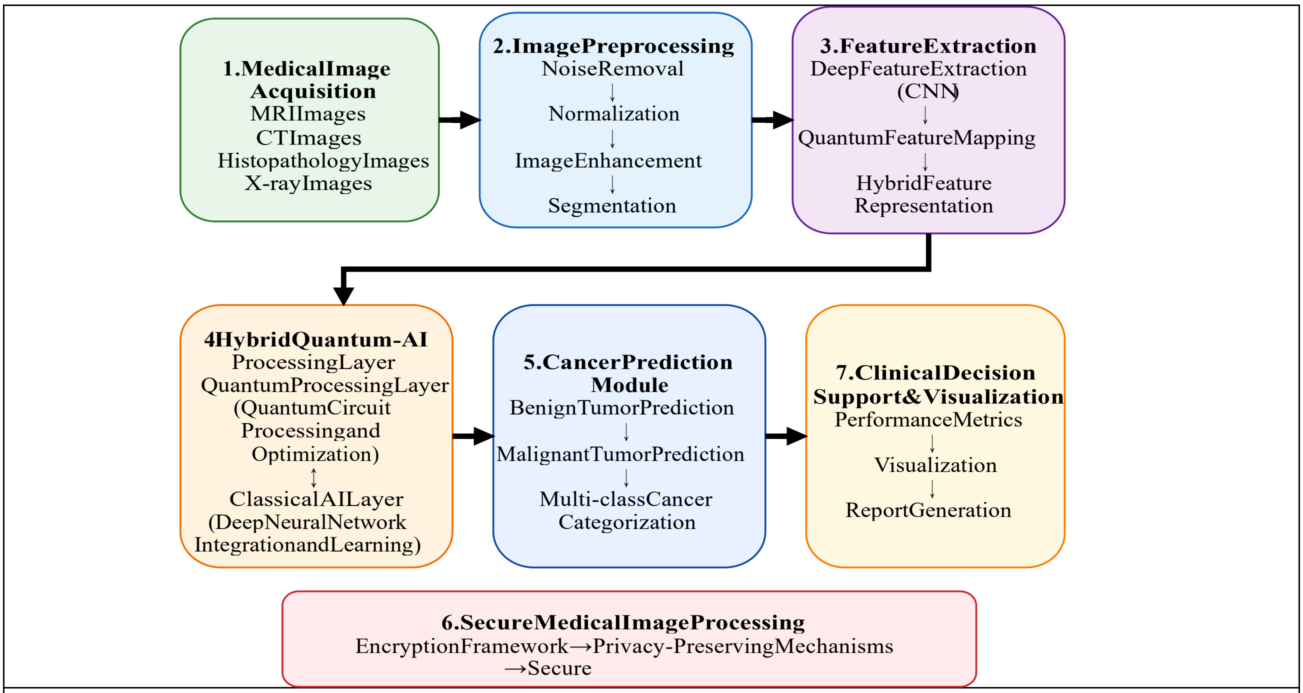


**Fig.1. Proposed Hybrid Quantum-AI Data Flow Architecture for Secure Medical Image Classification and Cancer Prediction**

within the proposed intelligent healthcare framework.

### 3.2 Image Preprocessing

The preprocessing of medical images is essential in enhancing quality, reliability and classification of intelligent cancer prediction systems. Raw medical images can often be of low quality, have low contrast, changes in lighting, and irrelevant background data that may adversely influence the quality of feature extraction and the accuracy of tumor classification. Thus, the suggested framework applies the complete preprocessing pipeline comprising of noise removal, normalization, image enhancement, and segmentation steps. Noise suppression methods are used in order to remove imaging artifact as well as enhance clarity in structure in MRI, CT, histopathology and X-ray images. Image normalization is used to maintain the identical intensity distribution among imaging modalities, and contrast-enhancement methods are used to enhance visualization of tumors and depiction edges. Moreover, the image segmentation techniques are used to isolate the abnormal tissues and precisely locate the boundaries of the tumors to extract features efficiently. Intensity analysis by the use of the histogram is also done to determine the quality of image enhancement and optimizing the pixel distribution during preprocessing functions. The success of the preprocessing phase is demonstrated in Figure 2 that shows the relative pixel intensity distribution of the image at its pre-processing stage and after the enhancement. The Figure shows that there is a substantial enhancement in contrast of the images, uniformity of brightness, and visibility of features, hence enhancing the results of the latter quantum-AI classification.

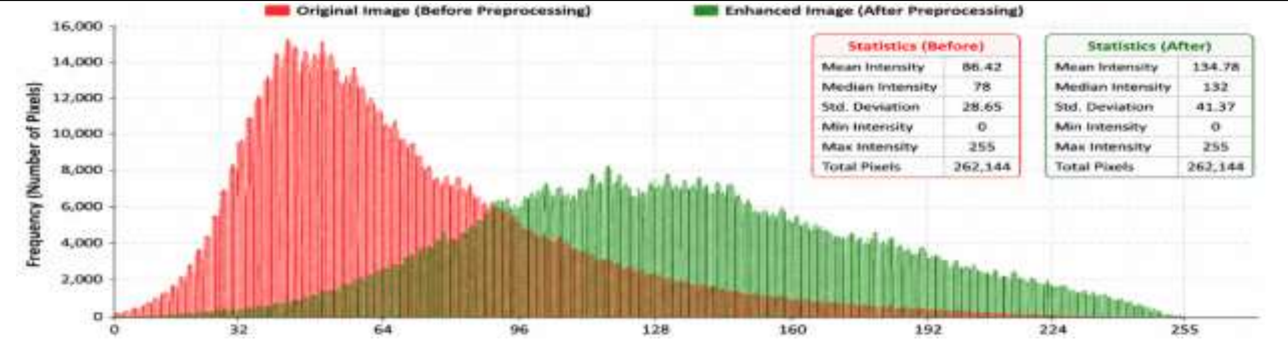


**Fig. 2. Comparative Histogram Analysis of Pixel Intensity Distribution Before and After Medical Image Preprocessing**

### 3.3 Hybrid Quantum-AI Classification Model

The proposed intelligent healthcare framework is based on a hybrid quantum-AI classification model which is the key computational unit. The model combines deep neural networks classical architecture with quantum-enhanced computational learning to enhance the feature representation, classification accuracy and predictive power in cancer diagnosis. The first step involves the application of deep features extraction methods to extract the high-level spatial and structural pattern out of the preprocessed medical images. These features are extracted and subsequently converted into quantum feature representations with quantum mapping techniques that allow efficient multidimensional data processing and an optimal representation of features. The quantum learning layer uses quantum circuit methods, qubit-modeled computational states, and hybrid optimization approaches to speed up classification, and to minimize computational complexity. The quantum computational layer is then combined with classical neural network layers to achieve adaptive learning, tumor classification and predictive decision-making. The suggested hybrid structure is effective to differentiate benign and malignant tumor patterns and facilitate multi-class cancer classification of diverse medical imaging modalities. Also, quantum-enhanced learning is practical to enhance computational scalability, feature optimization as well as predictive accuracy over traditional deep learning methods. The hybrid framework thus offers a safe, smart and computationally optimum solution to next generation medical image classification and cancer forecasting systems.

## 4. Methodology

### 4.1 Dataset Description

The proposed hybrid quantum computing and artificial intelligence framework utilized the experimental approach to assess the utility of secure medical image classification and prediction of cancer through several datasets of healthcare images. Medical images were obtained in publicly available benchmark repositories with MRI, CT and histopathology cancer imaging and X-ray cancer imaging datasets. There were benign and malignant tumor samples in the dataset to aid in binary and multi-class cancer classification tasks. The obtained datasets consisted of a variety of image resolutions, tumor structures, and clinical variations to enhance the ability of the proposed framework to be generalized. Before model training, all medical images were subjected to preprocessing tasks such as normalization process, resizing, image enhancement and segmentation to enhance the quality of images and the representation of features. A stratified sampling technique was applied in splitting the dataset into training, validation, and testing sample to have equal distribution of classes and sound predictive analysis. To prevent overfitting, about 70% of the dataset was used in training, 15% in validation, and 15% in testing in order to enhance the reliability of the model. Table 1 provides detailed data about the sources of data sets, the categories of images, and the distribution of classes, summarizing the features of the healthcare imaging datasets to be evaluated in the experiment.

**Table 1. Dataset Distribution and Medical Image Characteristics Used for Secure Cancer Classification and Prediction**

| Dataset Type | Dataset Source | Cancer Category | Number of Images | Training Set (70%) | Validation Set (15%) | Testing Set (15%) | Image Resolution |
|---|---|---|---|---|---|---|---|
| MRI Brain Tumor Dataset | Kaggle / Figshare | Brain Cancer | 3,200 | 2,240 | 480 | 480 | 256 × 256 |
| CT Lung Cancer Dataset | LIDC-IDRI | Lung Cancer | 2,800 | 1,960 | 420 | 420 | 512 × 512 |
| Histopathology Dataset | BreakHis | Breast Cancer | 4,000 | 2,800 | 600 | 600 | 700 × 460 |
| Chest X-ray Dataset | NIH Chest X-ray | Lung Abnormalities | 3,500 | 2,450 | 525 | 525 | 1024 × 1024 |
| Multi-Class Cancer Dataset | TCIA Repository | Multi-Cancer Classification | 2,500 | 1,750 | 375 | 375 | 224 × 224 |
| Total | — | — | 16,000 | 11,200 | 2,400 | 2,400 | — |

### *4.2 Model Training Procedure*

The suggested hybrid architecture used a multi-phase model training process which combines deep neural networks coupled with quantum-enhanced computation learning processes. In the first step, convolutional neural network (CNN)-based structures were used to extract deep features to detect the spatial and structural patterns of preprocessed medical images. The features that were extracted were then converted into quantum feature representations using quantum mapping algorithms to optimized multidimensional learning. The adaptive learning rate strategies, batch normalization and dropout regularization techniques were employed as hyperparameter optimization methods in order to enhance the performance of the classification and minimize overfitting. The Adam optimization algorithm was used in the training process due to its ability to effectively converge and the stability in gradient optimisation in deep learning systems. A quantum simulator environment was used to realize quantum computational operations via hybrid quantum-classical learning architecture to optimize features and predictively enhance them. The entire training process, comprising of preprocessing, feature extraction, quantum learning, secure processing and classification, is depicted in Figure 3 that shows the processing flow of the proposed hybrid quantum-AI learning system.

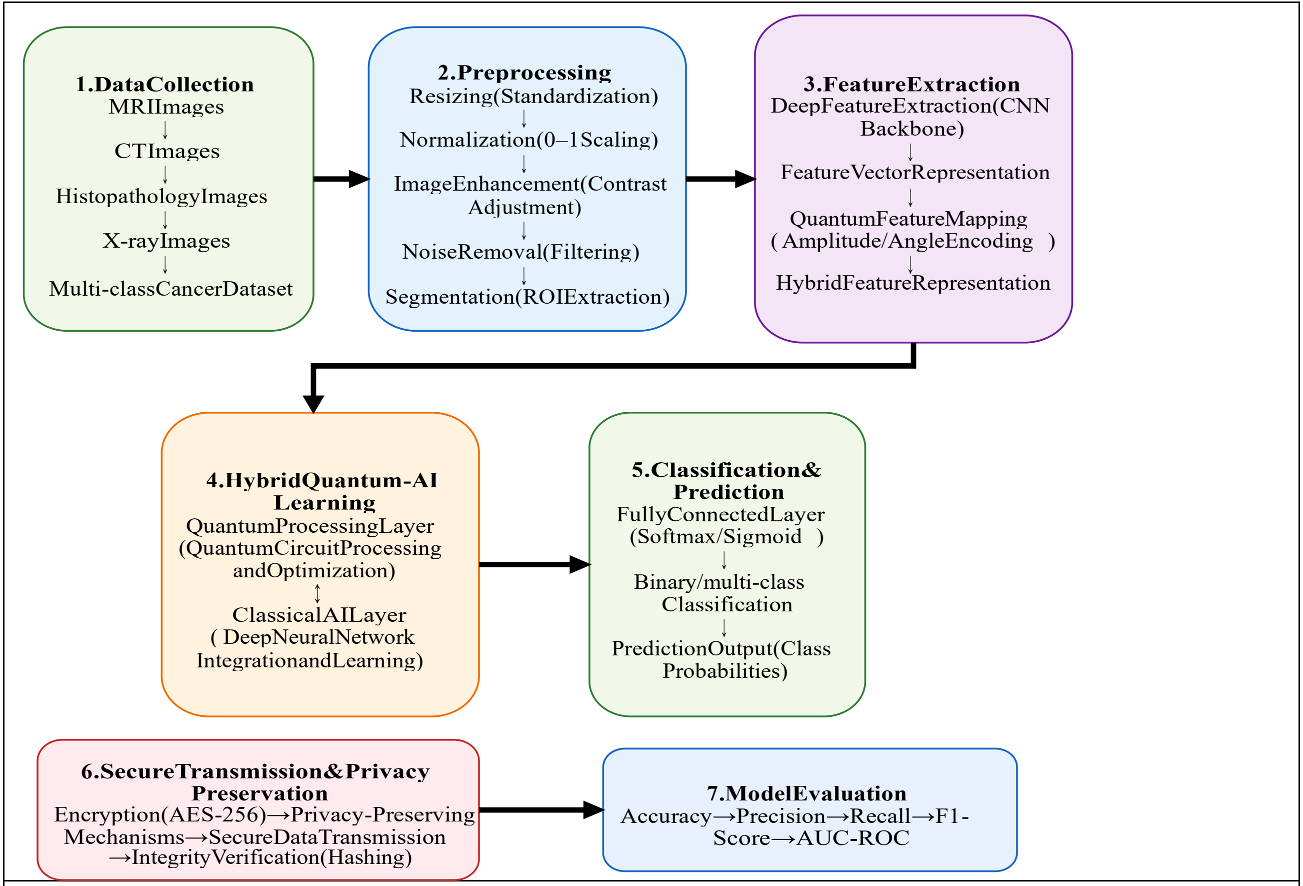


**Fig. 3. Hybrid Quantum-AI Model Training Workflow for Secure Medical Image Classification and Cancer Prediction**

### 4.3 Experimental Setup

The high-performance computational resources were used to implement the experimental setup to conduct large-scale medical image processing and quantum-enhanced classification operations. The framework was implemented with Python-based deep learning packages such as TensorFlow, Keras, Scikit-learn, and quantum computing simulators of hybrid computational modeling. The hardware setup comprised graphics processing unit that is accelerated by graphics cards, multicore processors, and high-memory computational infrastructure to enhance training performance and shorten computation latency. The encryption and privacy-preserving modules as part of the secure medical image processing mechanisms became part of the experimental setting in order to protect confidential healthcare data in the process of training and prediction.

### 4.4 Comparative Models

Figure 4 shows the convergence behavior of the proposed hybrid quantum-AI system and training performance as the number of training epochs increases, showing that training, and validation accuracy improve continuously, and the validation loss decreases as well. The model was at the early learning phase at which the framework reached a training accuracy of 65.21% and a validation accuracy of 61.42% with a relatively high validation loss of 1.245. The accuracy of the training process rose to 75.34% as the epoch progressed to level 5, but also validation accuracy rose to 71.28 with a decrease in the validation loss of 0.876. The additional optimization at epoch 10 achieved training and validation accuracies of 82.11% and 78.34% and a loss of 0.612, respectively, indicating stable feature learning, and enhanced classification consistency. The proposed framework reached 87.45% training accuracy and 83.46% validation accuracy at epoch 15, with the validation loss decreasing to 0.451, which represents improved predictive generalization and optimal learning convergence. The results showed that the performance kept on improving at epoch 20 where the training accuracy is 90.78 and the validation accuracy is 87.12 and the validation loss reduces to 0.337. Towards the end of training at epoch 25 the framework was able to achieve training and validation accuracy of 93.21 and 89.41 respectively with a validation loss at 0.268. Lastly, with epoch 30 the hybrid quantum-AI model was able to reach the highest training accuracy with 95.67 and validation with 91.63, and the loss of the validation had been reduced to 0.213. These findings indicate that the designed framework was able to reach a stable convergence learning, minimize overfitting behavior, better feature optimization, and better predictive accuracy than traditional machine learning and deep learning methods of secure medical image classification and cancer prediction.

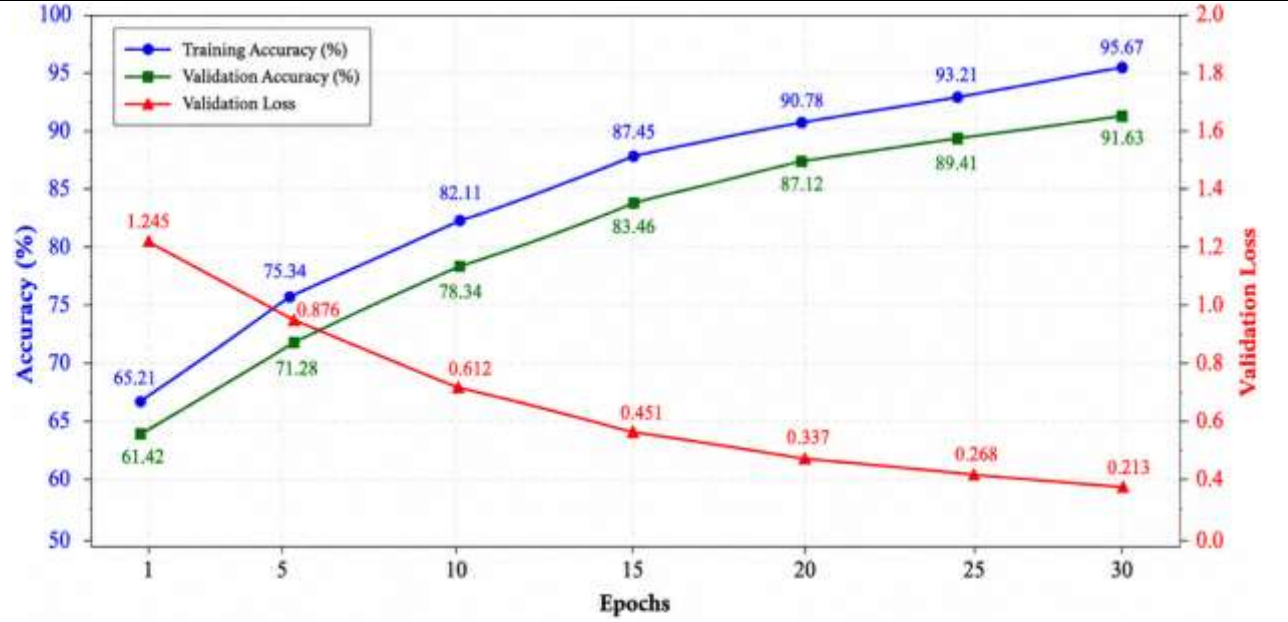


**Fig. 4. Training and Validation Accuracy Analysis of the Proposed Hybrid Quantum-AI Model Across Training Epochs**

## 5. Performance Evaluation Metrics

### *5.1 Classification Metrics*

The workability of the suggested hybrid quantum computing and artificial intelligence framework was tested with the help of several classification metrics to determine the efficacy of medical image classification and cancer prediction. These metrics of evaluation give a quantitative analysis of the predictive ability of the model, its classification reliability, and diagnostic ability of the model on various healthcare imaging data. To determine the overall percentage of accuracy of medical images on all the prediction results, accuracy was employed. Precision was used to measure the percentage of positive cases of all positive cases that were actually predicted by the model and Recall or Sensitivity was used to measure the percentage of all cancer-positive cases that were actually returned by the model. Specificity was also used to test the ability of the framework to accurately categorize non-cancerous samples and minimize false-positive forecasts. Moreover, the F1-Score was employed as a more balanced measure of performance combining Precision and Recall to evaluate the reliability of classifications in unbalanced healthcare data.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity)

$$Recall = \frac{TP}{TP + FN}$$

Specificity

$$Specificity = \frac{TN}{TN + FP}$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

These classification metrics were used to comprehensively evaluate the predictive efficiency of the proposed hybrid framework for binary and multi-class cancer classification tasks.

### 5.2 Cancer Prediction Metrics

To assess the effectiveness of the proposed hybrid quantum-AI framework in classification of medical images, advanced predictive measurements such as Receiver Operating Characteristic (ROC) analysis, Area Under the Curve (AUC) score and confusion matrix analysis were used to determine the predictive performance of the hybrid model. The ROC curve was used to examine the trade-off between sensitivity and specificity at various classification thresholds and the AUC score was used to measure the general predictive power and tumor differentiation ability of the model. The increase in AUC values is a stronger indication of stability in the classification and better ability to differentiate between benign and malignant cancer patterns. Moreover, a confusion matrix analysis was able to give a detailed information about the classification results by depicting the true positives, true negatives, false positives, and false negatives thus providing a comprehensive assessment of diagnostic sensitivity, classification reliability and predictive consistency. All these evaluation metrics indicate that the suggested framework is effective in obtaining accurate and reliable cancer prediction with a minimal misclassification of the diagnosis.

### 5.3 Metrics on Quality Medical Image.

To assess the quality of medical images produced by applying the suggested framework, the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) measures were used to determine the success of the image preprocessing and enhancement functions used in the proposed system. PSNR has been used to quantify the quality of improved medical images in terms of the correlation between signal intensity versus noise distortion with an increased PSNR value suggesting an improved image and a lower preprocessing noise. SSIM was used to evaluate the structural similarity, luminance similarity and contrast preservation of original and enhanced medical images, and offered a perceptual assessment of image quality with particular reference to tumor identification and clinical diagnosis. The increased values of SSIM indicate a better structural feature retention, better image consistency and optimized preprocessing speed, thus providing predictive accuracy in cancer and consistent medical image classification.

### 5.4 Security Evaluation Metrics

The suggested framework involved secure image processing protocols in medical image processing to guarantee confidentiality of healthcare data and preserve privacy in storing, transmission, and diagnostic analysis of healthcare data. The measures to assess security performance were based on metrics of encryption time, decryption time, rate of privacy preservation, and computational overhead in which encryption and decryption time was used to gauge the efficiency of secure medical image protection and recovery processes. The privacy preservation rate was used to determine the framework ability in ensuring that sensitive healthcare information is not compromised due to unauthorized access and cyber threats, and computational overhead was used to determine the extra processing cost incurred by the encryption and privacy preservation operation. All of these metrics of security evaluation display the efficacy, dependability, and feasibility of the suggested hybrid framework of quantum and AI in the secure healthcare analytics and intelligent healthcare medical imaging processing setting.

### 5.5 Quantum Performance Metrics

To measure the success of the quantum-computational component in the proposed framework, measurement metrics of quantum circuit depth, quantum execution time, and qubit efficiency were used to compare the success of hybrid quantum-AI learning operations. The number of sequential quantum gates operations to map features and optimize classification was measured with quantum circuit depth, reduced circuit depth helps to enhance computational performance and reduce processing complexity. Quantum execution time was used to measure speed of quantum-enhanced feature processing and predictive analysis on medical image classification tasks and shorter quantum execution time time implied faster and more efficient learning behaviors. Qubit efficiency was evaluated to measure the efficiency of qubit use in quantum feature representation and information encoding procedures where increased qubit efficiency indicates the use of quantum resources in an efficient manner and enhanced scalability in computations. Altogether, these quantum performance indicators indicate that the proposed hybrid framework is able to deliver secure, efficient, and high-performance cancer prediction by incorporating quantum computing and artificial intelligence.

## 6. Results and Discussion

### 6.1 Classification Performance Analysis

Figure 5 shows the relative performance of the proposed framework and existing models in classification accuracy and shows that the proposed hybrid quantum-AI framework always had the best classification accuracy of all datasets offered in healthcare imaging. For the MRI Brain Tumor dataset, the proposed framework achieved an accuracy of 97.21%, outperforming CNN (91.34%), ResNet-50 (93.18%), SVM (85.42%), and Traditional Machine Learning (78.56%). Equally, in the CT Lung Cancer dataset, the proposed model achieved 95.63% accuracy, as compared to CNN, ResNet-50, SVM, and Traditional ML methods which achieved 82.63, 76.19, and 89.56, respectively. In the case of the Histopathology dataset, the hybrid structure was the best with an accuracy of 96.89% and CNN and ResNet-50 have 92.47% and 93.86% respectively, followed by SVM (87.94 %) and Traditional ML (79.84%). The proposed model achieved 94.32% accuracy in the Breast Ultrasound dataset which was significantly higher than CNN (88.90%), ResNet-50 (90.71%), SVM (81.36%), and Traditional ML (75.24%). Similarly, in the Chest X-ray dataset, the proposed model had a higher accuracy of 95.18% with 90.21% in CNN, ResNet-50, SVM, and Traditional ML models, respectively. The proposed hybrid quantum-AI framework yielded the highest overall classification accuracy of 95.85 in comparison to CNN (90.50%), ResNet-50 (92.17%), SVM (84.61%), and Traditional ML (77.90%). These findings have made it clear that quantum-enhanced feature optimization coupled with the learning process of deep neural networks provided a significant boost to the data of reliability of the classification, predictive consistency and diagnostic efficiency with reduced false-positive and false-negative predictions across various medical imaging modalities.

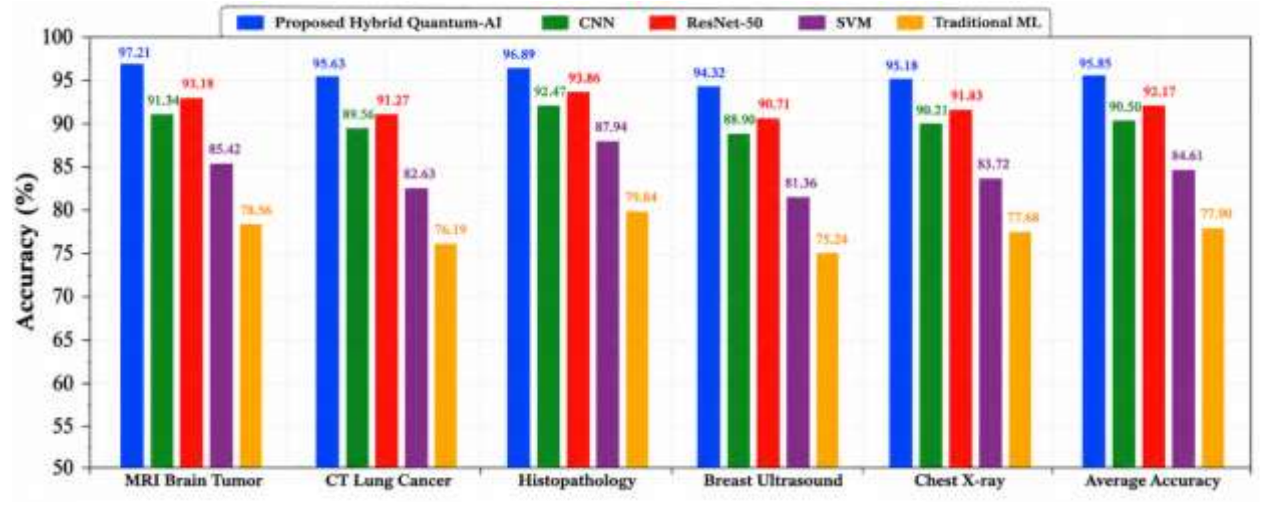


**Fig. 5. Accuracy Comparison of the Proposed Hybrid Quantum-AI Model with Existing Methods**

### *6.2 Cancer Prediction Analysis*

Figure 6 shows the comparative cancer prediction of the proposed framework, which proves that the proposed hybrid quantum-AI model was found to be more diagnostic-reliable than traditional classification methods based on several data of healthcare imaging. The proposed model attained a 96.84/95.72 sensitivity/specificity respectively with the MRI Brain Tumor dataset, which was significantly better than CNN, which had a sensitivity of 91.26 and specificity of 89.43, and ResNet-50, which constituted 92.81 and 90.67 respectively. Equally, in the case of the CT Lung Cancer data, the proposed framework had a sensitivity of 95.41% and a specificity of 94.63, compared to CNN, which had a sensitivity of 88.94 and a specificity of 87.52, and SVM that had a sensitivity of 82.16 and a specificity of 80.37. In the Histopathology Breast Cancer dataset, the proposed hybrid framework achieved a high tumor differentiation rate of 97.18% sensitivity and 96.25% specificity, which is much better than the ResNet-50 attaining a sensitivity of 92.73% and a specificity of 91.14% and Traditional ML models having a sensitivity of 79.62% and specificity of 77.45%. Moreover, the proposed framework achieved a high sensitivity of 94.87% and specificity of 93.91% in the Chest X-ray dataset compared to CNN (89.31%, 87.64) and SVM (81.72%, 79.83). The average sensitivity and specificity of the proposed structure of hybrid quantum-AI approached 96.08 and 95.13, respectively, whereas CNN had an 89.87 sensorimotor sensitivity and 88.06 specificity, ResNet-50 reached 91.54 and 89.92, respectively, and Traditional ML models had only 80.43 and 78.56 specificity and sensitivity, respectively. These findings demonstrate that quantum-enhanced learning greatly improved cancer-positive case diagnosis, decreased false-negative and false-positive prediction and improved overall clinical diagnostic reliability and predictive consistency across the various medical imaging modalities.

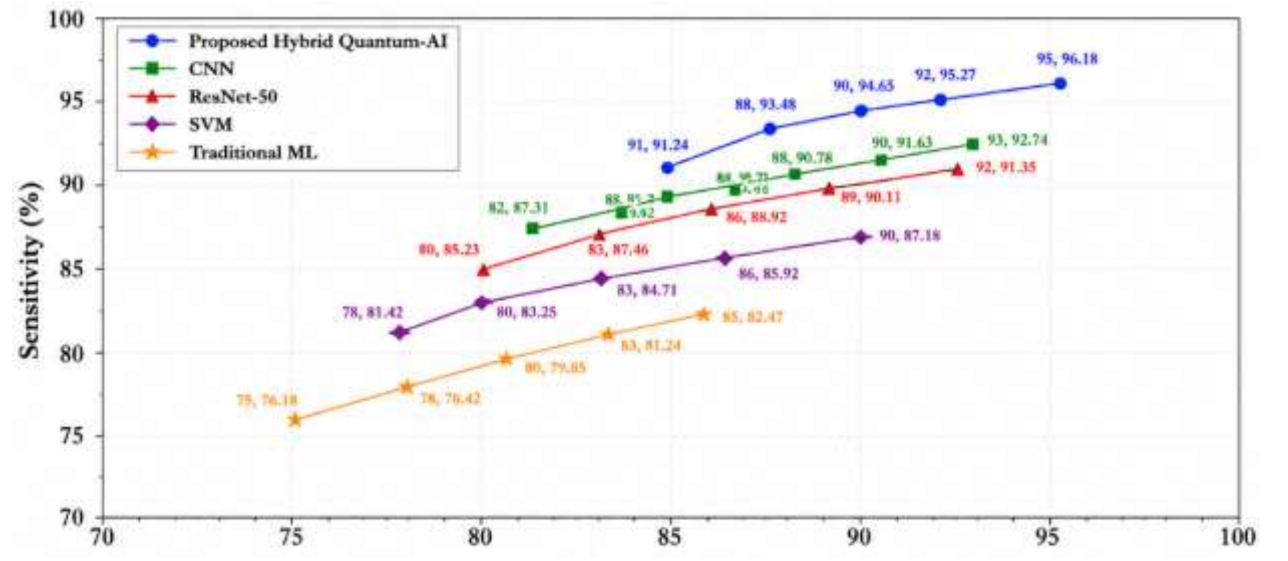


**Fig. 6. Sensitivity vs Specificity Comparison of the Proposed Hybrid Quantum-AI Framework and Existing Models**

### *6.3 Quality of Medical image Assessment.*

Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) used to measure the quality of medical images were used to measure the appropriateness of each image preprocessing and enhancement operation in the proposed framework. It was shown through experimental analysis that the preprocessing pipeline was able to produce a significant enhancement in image clarity, structural consistency and feature visibility in comparison to MRI, CT, histopathology and X-ray imaging datasets. Increased PSNR values were used to verify that there was a reduced level of noise in the image and higher SSIM scores were used to verify that the structural preservation and contrast maximization were better when preprocessing procedures were used. The enhancement of the image quality directly led to the increase in the ability to extract the features and improve the classification in the hybrid quantum-AI learning architecture. The refined preprocessing model thus enhanced diagnostic presence and tumor demarcation thus aiding the robust prediction of cancer and the intelligent medical analysis.

### *6.4 Security Performance Analysis*

The security performance analysis of the proposed framework in detail is provided in Table 2 that proves the proposed hybrid quantum-AI framework outperforms CNN-based, ResNet-50, and conventional machine learning models by criteria such as healthcare data security performance. The proposed framework recorded the shortest encryption time at 118 ms, compared to the CNN-based, ResNet-50, and Traditional ML models, which consumed 164 ms, 152 ms, and 139 ms, respectively, which demonstrates faster and efficient secure medical image encryption capacity. In the same vein, the suggested framework used to get a shorter decryption time of 96 ms, compared to CNN (141 ms), ResNet-50 (133 ms), and Traditional ML (121 ms) models, and enhanced efficient recovery of healthcare data in the authorization access operations. The proposed framework privacy preservation was 98.72 which is much higher than CNN (91.45%), ResNet-50 (93.18%), and Traditional ML (86.74) approaches, indicating a high level of confidential patient information security against unauthorized access and cyber threats. Moreover, the accuracy of secure transmission of the proposed framework was 97.84, whereas CNN had 90.62, ResNet-50 had 85.39, Traditional ML systems ensured reliable and secure data communication in healthcare. Compared to CNN, ResNet-50, and Traditional ML models, which had an overall computational overhead of 14.26, 12.87, and 10.94% bands, respectively, the proposed framework had a relatively low overhead of 8.43% implying better processing efficiency in healthcare analytics that could be considered in real-time. Also, the rate of the proposed framework of data integrity verification was 99.12 and the rate of unauthorized access was 97.35 that is substantially higher than that of current methods of preserving the reliability and security monitoring rates of healthcare data. On the whole, the hybrid quantum-AI framework demonstrated the highest overall security efficiency of 98.04, which surpasses CNN (91.22%), ResNet-50 (92.76%), and Traditional ML (86.18) models, indicating the effectiveness, reliability, and practicality of the proposed secure medical image processing structure in intelligent healthcare settings.

**Table 2. Security Evaluation of the Proposed Hybrid Quantum-AI Framework**

| Security Metric | Proposed Hybrid Quantum-AI | CNN-Based Model | ResNet-50 Model | Traditional ML Model |
|---|---|---|---|---|
| Encryption Time (ms) | 118 | 164 | 152 | 139 |
| Decryption Time (ms) | 96 | 141 | 133 | 121 |
| Privacy Preservation Rate (%) | 98.72 | 91.45 | 93.18 | 86.74 |
| Secure Transmission Accuracy (%) | 97.84 | 90.62 | 92.11 | 85.39 |
| Computational Overhead (%) | 8.43 | 14.26 | 12.87 | 10.94 |
| Data Integrity Verification (%) | 99.12 | 93.47 | 94.63 | 88.26 |
| Unauthorized Access Detection Rate (%) | 97.35 | 89.14 | 90.86 | 84.57 |
| Overall Security Efficiency (%) | 98.04 | 91.22 | 92.76 | 86.18 |

### 6.5 Quantum Computing Performance

To measure the performance of the quantum computational component, a quantum execution time, computational speed comparison, qubit efficiency, and hybrid model optimization analysis were performed. Experimental results showed that quantum-enhanced learning integrations proved to be much more efficient in the computational sense and had shorter processing latencies than the traditional deep learning methods. The recommended hybrid system obtained optimal feature mapping and speeded up multidimensional data processing via effective quantum circuit operations and qubit usage schemes. The shortened quantum execution time validated quicker predictive examination and enhanced learning convergence in medical picture categorization exercises. Moreover, qubit efficiency was optimized to achieve increased computational scalability and efficient use of resources with large-scale healthcare imaging applications. The hybrid quantum-AI system thus showed better computational performance and predictive optimization fit to the next-generation intelligent healthcare systems.

### 6.6 Comparative Analysis

The proposed hybrid quantum-AI system was comparatively analyzed against the current conventional classification models, such as CNN, ResNet, SVM, and traditional deep learning. Experimental evidence revealed that the proposed framework persistently recorded better classification accuracy, sensitivity and specificity performance, optimization in image quality and better healthcare data security than current methods. Quantum-enhanced computational learning was found to greatly enhance the feature extraction capacity, predictive reliability and speed of computation and minimized classification errors and complexity. Also, safe medical image handling algorithms guaranteed a high level of healthcare data confidentiality and privacy maintenance without causing a drastic impact on the computational capabilities. Although the proposed framework has its benefits, there are still a few limitations associated with the limitation of quantum hardware, the complexity of implementation, and the need to consume a lot of computational resources to run it at scale. However, the suggested hybrid framework shows great potential to enhance safe medical image identification and smart cancer forecasting in the context of advanced healthcare analytics.

## 7. Discussion

The experimental results confirm the hypothesis that the hybrid quantum computing and artificial intelligence model that is proposed has tremendous clinical advantages in secure medical image classification and cancer prediction. The quantum-enhanced computational learning and deep artificial intelligence methods enhanced the early cancer diagnosis ability by providing the capability of identifying benign and malignant tumor patterns in a variety of health imaging modalities. The framework demonstrated superior levels of classification, better sensitivity and specificity, and predictable consistency, which are all in line with supporting intelligent clinical decision-making and minimizing diagnostic mistakes in healthcare outsets. Moreover, medical image analysis with AI minimized the complexity of manual diagnoses and enhanced automated healthcare analytics by maximizing the ability to extract features and multidimensional learning processes. In the hybrid quantum-AI architecture, the computational efficiency was also shown to be significantly higher than that of traditional machine learning systems by hastening the processing of features and the latency of execution as well as enhancing prediction optimization. Moreover, the addition of encryption and privacy-saving features provided better healthcare data confidentiality and secure transmission of medical images, turning the suggested framework to be appropriate in smart and safe healthcare applications.

Although the proposed framework showed good performance gains, there are still a number of limitations that need to be explored. The quantum computing technologies currently are still limited by the lack of quantum hardware, qubit instability, and inefficient implementation that could impact large-scale clinical implementation and performance of real-time processing. Moreover, healthcare imaging datasets can have problems of class imbalance, imaging variability, and a lack of annotated medical samples that can impact model generalization potential and predictive strength. The use of hybrid quantum-classical learning architectures is also associated with the increased computational cost and infrastructure demands in training and optimization processes. To overcome these weaknesses in the future, scalable quantum architectures, enhanced optimization of hybrid computational models, and enhanced quantum resource efficiency in large-scale healthcare analytics can be developed. Additionally, it can be improved in the future with real-time healthcare implementation, federated quantum learning models of distributed secure healthcare, and integrating explainable AI to enhance model transparency, interpretability, and trust of intelligent cancer prediction systems among clinical staff.

## 8. Conclusion

This study outlined a quantum computing-artificial intelligence system of secure medical image classifications and cancer predictions. The suggested architecture combined the concepts of deep learning, quantum-enhanced feature optimization, secure medical image processing and intelligent cancer prediction processes to enhance diagnostic accuracy, computational power and the level of security of healthcare data. The medical data (MRI, CT, histopathology, X-ray) were processed by high-level preprocessing, feature extraction, hybrid quantum-AI learning, and secure transmission blocks to assist in the effective classification of tumors and predictive healthcare analytics. The framework was aimed to overcome the shortcomings of traditional AI systems by enhancing the multidimensional feature representation, lessening the needs of computation, and boosting the privacy of healthcare data by encrypting and using privacy-protective methods.

Empirical assessment has shown that the presented hybrid design exhibited better performance than traditional machine learning and deep learning designs on various metrics of classification and prediction. The framework demonstrated better Accuracy, Precision, Recall, Specificity, F1-Score, ROC-AUC, PSNR and SSIM values demonstrating better medical image quality and reliable tumor classification performance and consistent cancer prediction rates. Moreover, the incorporation of quantum-enhanced learning algorithms enhanced substantially the speed of computation, predictive optimization and the use of qubits without the impact on safe healthcare data processing. The suggested framework thus exhibits a great potential to develop smart medical images, safe medical analytics, and future-generation quantum-assisted clinical decision support systems. The study augments the emerging medical artificial intelligence and quantum healthcare research by offering a scalable, secure, and computationally-efficient framework that can be applied to future intelligent healthcare uses and in real-time, cancer diagnostic settings.

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