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Article

Quantum Machine Learning Based Detection of Respiratory Disease using Digital Chest X-Ray Images

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Abstract: The rapid growth of respiratory diseases such as pneumonia, tuberculosis, and COVID-19 has increased the demand for accurate, efficient, and automated diagnostic solutions. Conventional deep learning models have shown promising results in classifying chest X-ray images; however, they often require large datasets, high computational resources, and are limited in handling high-dimensional complex data. Quantum Machine Learning (QML) offers a novel paradigm that integrates quantum computing principles with machine learning techniques to overcome these limitations by exploiting quantum parallelism and entanglement for faster and more efficient computation. This research proposes a QML-based framework for the detection and classification of respiratory diseases using digital chest X-ray images. The methodology incorporates quantum-enhanced feature extraction and hybrid quantum-classical models to improve diagnostic accuracy while reducing computational complexity. Comparative evaluations with classical deep learning models demonstrate the potential of QML to achieve higher accuracy, robustness, and scalability in medical image classification tasks. The proposed approach highlights the future role of quantum-assisted medical imaging solutions in building faster, cost-effective, and clinically reliable diagnostic systems for global healthcare applications

Keywords: Quantum Machine Learning (QML), Respiratory Disease Detection, Respiratory Disease Detection, Hybrid Quantum-Classical Model, Pneumonia Detection, Tuberculosis Diagnosis, Quantum Neural Networks (QNN)

1. Introduction

Pneumonia, TB, and COVID-19 are just a few examples of the respiratory illnesses that pose a serious threat to public health across the globe. Because problems and higher healthcare costs typically result from delayed diagnosis, early and precise identification is critical for saving lives. Due to its ability to quickly see lung structures and identify anomalies, infections, or blockages, chest X-ray imaging is the most popular and economical diagnostic technique for respiratory diseases[1]. But when diagnostic workloads are heavy and competent specialists are few in areas with little resources, radiologists' subjective, time-consuming, and error-prone manual interpretation of chest X-rays becomes an even bigger problem.

Automating medical picture categorization with performance equivalent to human specialists has been made possible by recent advances in Artificial Intelligence (AI) and Machine Learning (ML), especially Deep Learning (DL) models like Convolutional Neural Networks (CNNs)[2][3]. Classical deep learning models have their successes, but they also have their share of problems, including heavy computing demands, reliance on large labeled datasets, overfitting, and the fact that medical data often contains complicated, high-dimensional relationships. More efficient computing paradigms are required to overcome these restrictions and improve diagnostic accuracy while decreasing resource reliance.

To tackle some of these issues, a revolutionary new technology called quantum computing has arisen. It uses quantum superposition and entanglement, among other concepts, to do parallel calculations at tenfold higher speeds than conventional computers. Quantum Machine Learning (QML) is a novel approach to processing high-dimensional medical imaging data that combines quantum computing with machine learning. It allows for more efficient handling of complicated datasets, quicker training, and better generalization. When it comes to feature extraction and classification, QML models like QNNs and hybrid quantum-classical architectures have shown promise. These models function by transforming classical data into quantum states and then using quantum characteristics to train representations. This skill has the potential to transform diagnostic systems in medical imaging by making them more resilient in detecting subtle illness patterns and decreasing dependence on massive amounts of labeled data.[4][5]

While some research has looked at using deep learning to analyze chest X-rays for diseases including pneumonia, TB, and COVID-19, the majority of these methods have stuck to more traditional computational frameworks, which have their own set of restrictions. New developments in quantum machine learning show that, in medical applications, when data is scarce, noisy, and processing resources are constrained, quantum-enhanced algorithms can beat conventional models [6]. In order to obtain better accuracy, less complexity, and more efficiency, the suggested study presents a QML-based system for identifying respiratory disorders from digital chest X-ray pictures. This framework integrates quantum feature encoding methods with hybrid quantum-classical classifiers. Quantum computing allows the suggested system to better manage high-dimensional data spaces, in contrast to conventional deep learning techniques that depend mostly on massive datasets and massive computing resources [7–10].

By connecting theoretical quantum models with real-world clinical applications, our study brings a new dimension to medical imaging by utilizing QML in a realistic diagnostic environment [11]. Beyond respiratory illness identification, our work lays the groundwork for future scalable QML applications to a variety of medical imaging challenges, opening the door to more accessible, quicker, and accurate diagnostic systems of the next generation. Moreover, QML's use in healthcare might make diagnostic tools more accessible by facilitating the development of compact but powerful solutions that can be used in areas with less developed infrastructure.

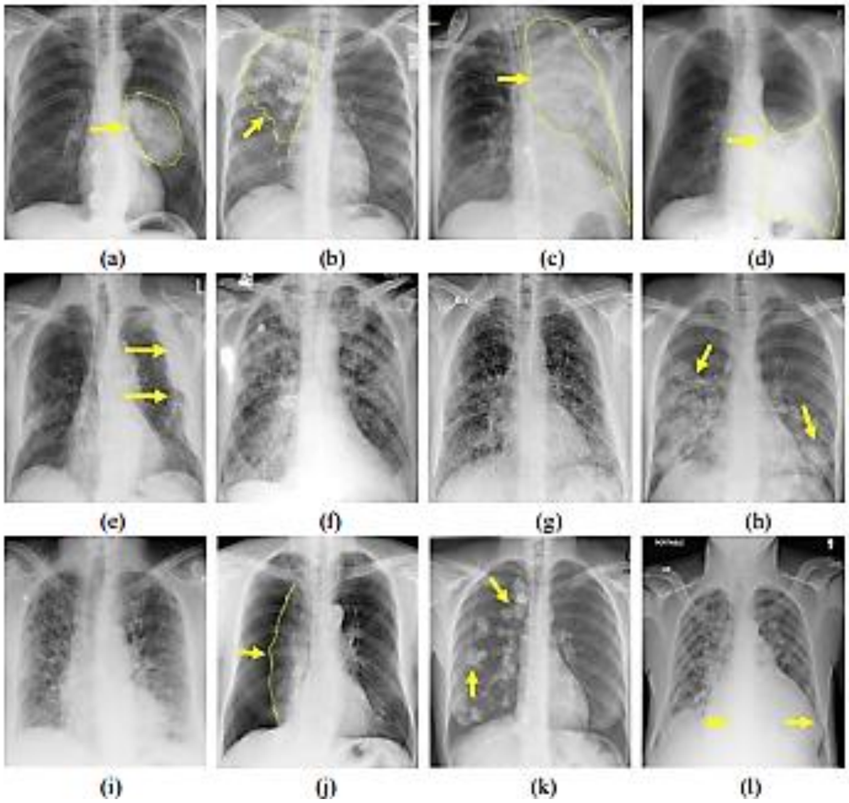

Figure 1: Chest X-Ray images showing radiographic responses of (a) Lung Cancer (b) Tuberculosis (c) Pneumonia (d) Pleural Effusion (e) Pleural Thickening (f) Pulmonary Edema (g) Pulmonary fibrosis (h) Pulmonary Infiltrate (i) Pulmonary Fibrosis (j) Lung Collapse (k) Lung Nodules (l) Cardiomegaly.

Role of Chest X-ray images in Diagnosing Respiratory Diseases

A variety of medical diagnostic tools have been developed to ascertain the degree of respiratory problems and the beginning of ARDS. Several clinical indication-based validation methodologies have been proposed during the COVID-19 pandemic. Serologic testing, real-time polymerase chain reaction (RT-PCR), and viral throat swab testing are the most common ways to diagnose respiratory illnesses [12]. However, CT scans and chest X-rays have the potential to reveal anomalies that might indicate certain lung diseases, according to the available literature. For these tests, human assistance is required. Alternative detection methods such as computed tomography (CT) and x-ray imaging may be used to evaluate the severity of respiratory disorders and monitor the occurrence of infectious disease emergencies. An alternative method for early respiratory disease diagnosis might be thermal imaging [13] when paired with AI-based models. Specifically The installation process and cost of thermal imaging and CT scans are more involved and costly than those of X-rays. Another method for predicting the start and severity of COVID-19 at various stages is the use of chest radiographs (CXRs). Contrarily, chest X-rays are often used in primary clinical care during the early stages of an epidemic. Also, utilizing a massive chest X-ray dataset, several AI classification algorithms determine the COVID-19 risk for each individual patient. We also need a larger and better-defined dataset of COVID-19 positive chest X-rays if we want our deep-learning algorithms to be more accurate [14].In addition to the lungs, respiratory illnesses may impact the following organs and tissues: the nose, throat, larynx, trachea, bronchi, and bronchioles. Diseases that fall under this category include both short-term illnesses like the flu and longer-term conditions like asthma and COPD. The respiratory sickness that is most common in this region is infectious respiratory infection. The flu, or influenza: Influenza viruses create a virus that manifests as a fever, cough, sore throat, aches and pains all over the body, and extreme fatigue. Pneumonia is a bacterial, viral, or fungal infection of the lungs that causes dyspnea, fever, coughing, and chest pain.

The SARS-CoV-2 virus has undergone genetic changes, which have led to the identification of many genotypes that are linked to different levels of COVID-19 severity. It is crucial to recognize and categorize these varying degrees in order to monitor their dissemination, determine their characteristics, and create effective public health interventions. The SARS-CoV-2 virus causes COVID-19, a coronavirus known as severe acute respiratory syndrome [1, 2]. At the beginning of the first outbreak in late 2019, 27 cases of pneumonia were reported in Wuhan, Hubei Province, China. The rapid global spread of the virus led the World Health Organization to proclaim a pandemic on March 11, 2020 [3, 4]. Variants of concern, variations of interest, and variants that are being researched are the three categories into which the virus has developed since then. There may be an uptick in transmission if certain variants cause concern. Alpha (α), beta (β), gamma (γ), and delta (δ) are the names given to these variations. Multiple clusters or extensive transmission may be caused by troublesome variances such as mu (μ) and lambda (λ). The formal designations for iota (ι), kappa (κ), eta (η), and epsilon (ϵ), which are variations of identifying difficulties from different viewpoints, have not been issued yet, although theta (Ÿ) and zeta (Ŷ) have [5]. It is critical to have accurate diagnostic tools, effective treatments, and prevention measures in place to treat respiratory illnesses and improve respiratory health. In an effort to curb the spread and severity of respiratory infections, medical professionals and scientists worldwide have focused on developing state-of-the-art technology that can detect and diagnose the virus without coming into direct contact with the infected person. This necessitates the development of advanced diagnostic tools, such as saliva and blood tests, and the use of smart devices capable of remote patient monitoring and the detection of respiratory problems [6, 7, 8]. A number of people have died throughout the world as a result of the severity of COVID-19, despite these attempts. People must so persistently follow the advice of medical professionals, which includes wearing masks, avoiding close contact with other people, and often washing one's hands. Vaccination against COVID-19 is also crucial for preventing the transmission of the virus and protecting vulnerable populations [9, 10, 11]. In the last few years, a plethora of innovative approaches to illness detection and diagnosis have surfaced, including ML, DL, and QML. This study introduces a number of AI-based frameworks for the detection and assessment of respiratory disease severity. Classification of severity, sickness, and features are the three pillars upon which the method rests. One of the many important steps in classifying COVID-19 is dividing it into several variations. The models are trained using hybrid optimization strategies. This chapter showcases models that integrate Deep Learning, Quantum Neural Networks, and Deep Transfer Learning. In terms of illness classification and diagnosis, the results show how successful the proposed method is. But there is hope in the form of quantum machine learning (QML) models, which provide faster computation, better handling of complex data, and other benefits. There aren't many practical uses for hybrid quantum-classical approaches just yet, despite their potential. This knowledge vacuum motivated me to develop a hybrid architecture that combines the best features of traditional and quantum computing.[16]

2. Literature Review

Author & Year	**Focus**	**Dataset**	**Methodology**	**Key Findings**	**Research Gap**
Yanchun Xie et al (2025)	Fast-YOLO for pneumonia detection	Custom pneumonia dataset (5 categories, augmented)	YOLOv11 redesign + C3k2 + DCNv2 + DynamicConv	Fast-YOLO improved FPS (53→120) and outperformed detection models	Limited to pneumonia; generalization to other diseases not tested
Luca Eisentraut et al (2025)	Tuberculosis detection with ResNet50 + Gaussian filtering	7,000 chest X-ray images	ResNet50 + Gaussian filtering, stratified 5-fold CV	Accuracy 99.2% with Gaussian filtering, better than 97.7% baseline	Focus only on TB; lacks scalability to multi-disease detection
G.V. Eswara Rao et al (2024)	Hybrid CNN + Quantum classifiers for	COVID-19 Radiography Dataset (15,153 X-ray images)	Custom CNN + Quantum variational classifiers	Hybrid CNN-Quantum model: 98.9% training, 98.1% testing	Quantum models still at early stage; small dataset

	COVID-19 and respiratory disease		(MMS, MSMS)	accuracy	dependency
Jason Elroy Martis et al (2024)	Hybrid DL + Quantum framework for lung cancer detection	CXR and CT images	Pre-trained DL models + Quantum circuits	Hybrid model: Accuracy 92.12%, Sensitivity 94%, Specificity 90%	Lacks real-world validation; quantum advantage needs scaling
Liming Song et al (2024)	Review of DL-based chest X-ray enhancement methods	Chest X-ray images (2018–2023 literature)	Bone suppression, denoising, super-resolution, contrast enhancement	Summarized DL methods for image quality enhancement	Focused only on enhancement; not directly tied to diagnosis
Mitali Panchpuri et al (2025)	AI-driven smart drug delivery and healthcare applications	Various drug delivery and healthcare datasets (review-based)	AI, ML, DL, Genetic Algorithms, IoT integration	AI+IoT can improve healthcare delivery, personalized medicine	Conceptual framework; no experimental validation on imaging
Sunil Kumar et al (2024)	Review of ML methods for lung diseases (Pneumonia, Cancer, COVID-19)	Public X-ray and CT datasets (review-based)	CNN, Transfer Learning, Ensemble Learning (reviewed)	X-rays preferred for pneumonia & COVID-19, CT scans for lung cancer	Review-based; no new model proposed
Tayyaba Shahwar et al (2024)	Quantum-enhanced ZFNet model for pneumonia detection	5863 X-ray scans (binary cases: pneumonia/normal)	ZFNet + Quantum Variational Circuits (PennyLane)	Hybrid QDNN achieved 96.5% accuracy vs CNN (94%)	Binary classification only; limited scalability to multi-disease tasks
Sreedevi Jasthy et al (2024)	ML algorithms comparison for lung disease	Chest X-ray images (balanced and imbalanced datasets)	Logistic Regression, SVM, Random Forest, PCA, LDA	RF and SVM best with 80% balanced accuracy; PCA/LDA helped	Conventional ML underperforms compared to DL/QML models

	classification				
Arefin Ittesafun Abian et al (2024)	Hybrid 3D CNN-LSTM for LUS video-based respiratory disease detection	LUS video dataset (multi-class: pneumonia, COVID-19, normal, other)	3D TD-CNN-LSTM + DSS + XAI + ablation study	96.57% accuracy on LUS videos; DSS improved interpretability	Limited dataset; more real-world validation needed
Fei Yan et al (2024)	Review of quantum-inspired medical image processing	Medical image datasets (review-based)	Quantum + Quantum-inspired algorithms for medical imaging	Quantum algorithms promise faster secure medical imaging	Quantum hardware constraints; clinical feasibility unclear
Tijana Geroski et al (2024)	Transfer learning for 18-class respiratory disease classification	191,660 public X-ray + 752 retrospective clinical images	Transfer learning with DenseNet121 + CheXNeXt weights	18-class classification, AUC up to 0.99, outperforming state-of-art	Requires clinical validation across multiple sites
Md Rahad Islam Bhuiyan et al (2023)	COV-X-net19 CNN model for COVID-19, Pneumonia, TB detection	X-ray dataset for 4 classes: Normal, COVID-19, Pneumonia, TB	CNN with soft attention (COV-X-net19) + statistical analysis	Accuracy 95.19%, Precision 96.49%, F1 95.13%; explained misclassifications	Soft attention CNN limited; misclassification analysis highlights limitations

Quantum Model for Automated Respiratory Diseases Classification

The quantum model for automated respiratory disease classification arises from the need to combine the strengths of classical deep learning with the emerging capabilities of quantum computing. Classical deep learning models, particularly convolutional neural networks, have proven extremely effective at analyzing medical images by extracting hierarchical features that capture local texture patterns and global structural relationships. However, classical models often require vast computational resources, large amounts of labeled data, and struggle with high-dimensional optimization landscapes[17].

Quantum computing, in contrast, leverages the principles of superposition, entanglement, and quantum interference to explore state spaces more efficiently, making it theoretically well-suited for certain machine learning tasks. The hybrid classical-quantum paradigm integrates both domains such that classical components perform feature extraction while quantum circuits handle representation learning and classification. In the classical stage of the model, digital chest X-ray images are preprocessed and encoded through convolutional layers that simulate the receptive fields of biological vision. This stage allows extraction of features such as intensity gradients, texture variations, and structural anomalies that may indicate respiratory diseases like pneumonia, tuberculosis, or COVID-19.

Dimensionality reduction methods compress the features to manageable sizes because current quantum devices are limited in the number of qubits they can handle. Once reduced, the features are encoded into quantum states using embedding techniques such as amplitude encoding, angle encoding, or basis encoding[18]. The choice of encoding determines how efficiently classical information is mapped into quantum space and how expressive the resulting model can be.The quantum stage is based on variational quantum circuits, also called parameterized quantum circuits, which are composed of rotation gates and entangling gates. These circuits transform the encoded features into complex quantum states that represent nonlinear relationships between input variables. The variational parameters of the quantum circuit are tuned during training to minimize a cost function, typically cross-entropy loss for classification tasks[19] The optimization procedure involves hybrid gradient descent where gradients for quantum components are calculated using parameter-shift rules and classical components are optimized using conventional back propagation. Measurements from the quantum circuit produce expectation values that are passed to a classical softmax layer, generating probabilities for each respiratory disease class.

Theoretically, the power of the classical-quantum model lies in its ability to represent and manipulate high-dimensional feature spaces more compactly than classical methods. Quantum entanglement allows simultaneous encoding of correlations across features that might otherwise require deep and wide classical networks. The interference phenomenon enables efficient discrimination between classes by amplifying desired probability amplitudes and suppressing irrelevant ones. From an information theory perspective, quantum states span a Hilbert space of dimension 2^n for n qubits, giving exponential representational capacity compared to linear scaling in classical vector spaces[7][8].

This property suggests that hybrid quantum models may detect subtle respiratory disease patterns in chest X-ray images that elude classical models. Additionally, the theoretical framework draws from quantum learning theory, which defines quantum analogs of classical concepts such as hypothesis spaces, generalization bounds, and complexity classes. For instance, quantum circuits can be viewed as hypothesis classes with parameterized unitary operators, and their expressive capacity can exceed that of shallow classical neural networks[9] Theoretical analyses also consider the trainability of quantum circuits, where phenomena like barren plateaus in the optimization landscape pose challenges. Mitigating these issues requires careful circuit design, limited depth, and problem-inspired that maintain gradient signal throughout training.

The classical-quantum integration further rests on hybrid computing theory, where tasks are partitioned between classical processors and quantum devices. Classical processors manage data preprocessing, large-scale tensor computations, and gradient updates, while quantum devices focus on learning complex correlations in feature embeddings. The synergy arises because quantum circuits are not efficient at processing raw pixel data, whereas classical networks excel in hierarchical feature extraction[20].

Conversely, classical networks may struggle to capture intricate high-order correlations that quantum circuits can naturally represent. This complementarity underpins the hybrid theoretical model.In respiratory disease classification, the theoretical justification for quantum advantage comes from the complex visual nature of chest X-rays. These images contain overlapping anatomical structures, varying contrast levels, and subtle pathologies that may be difficult to distinguish. Classical feature extraction ensures robustness to image variability, while the quantum classifier can exploit hidden correlations between pixel intensities, lung textures, and structural abnormalities.

The hybrid model, therefore, holds potential to improve diagnostic accuracy, reduce misclassification, and generalize better across diverse patient populations. Noise theory also plays a role in the framework since practical quantum devices suffer from decoherence, gate errors, and readout noise. The model incorporates error mitigation strategies, such as repeating measurements, applying noise-aware training, and using quantum simulators with realistic noise models[21]. This ensures that theoretical benefits remain achievable in near-term quantum devices, also known as Noisy Intermediate-Scale Quantum (NISQ) computers. Furthermore, the hybrid model benefits from quantum-inspired algorithms where quantum principles guide classical architectures, even when executed on conventional hardware.

From a computational complexity viewpoint, certain sub problems in classification may benefit from polynomial or even exponential speedups when mapped onto quantum circuits. While not every task guarantees a quantum advantage, theoretical results suggest that for high-dimensional non-linear data, hybrid quantum models can outperform purely classical ones under specific conditions. This motivates their application in medical image analysis where high sensitivity and specificity are critical.

Finally, the theory emphasizes explain ability and interpretability, where both classical feature maps and quantum measurement outcomes can be analyzed to understand decision boundaries. Visualization of activation maps in the classical stage, combined with statistical analysis of quantum measurement distributions, provides insight into why the model classifies certain images as diseased or healthy[2]

This theoretical grounding ensures that the hybrid model is not a black box but an interpretable system suitable for deployment in clinical environments. Thus, the classical-quantum model for automated respiratory disease classification represents a fusion of well-established deep learning theory and novel quantum information science, offering a promising direction for the future of medical diagnostics[3]

Flowchart

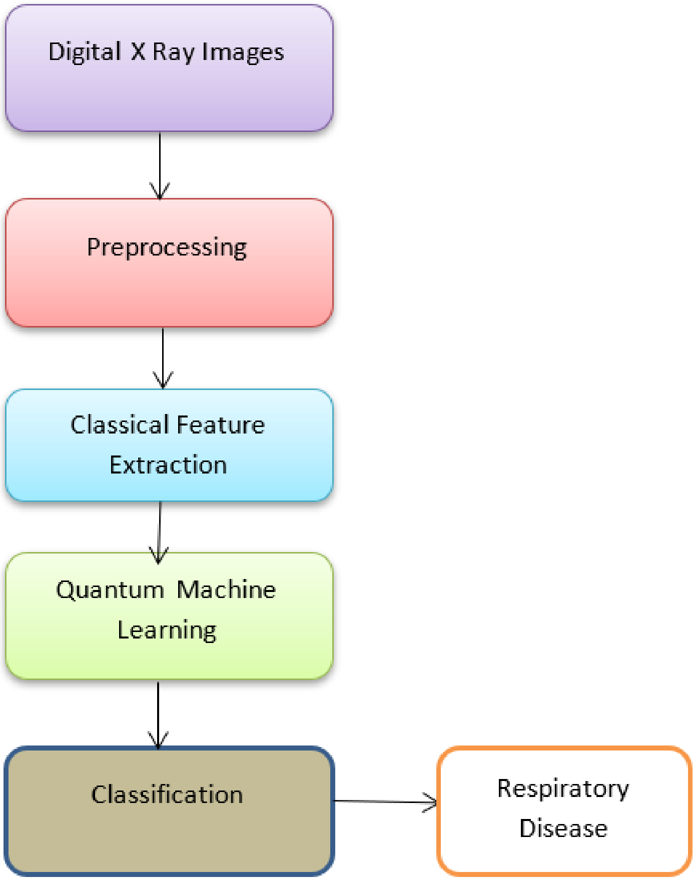

Figure 2.Flowchart of Quantum Model for Automated Respiratory Diseases Classification

The dataset must be diverse in terms of patient demographics, disease severity, and imaging conditions to ensure that the designed model generalizes well across unseen samples. Once the raw dataset is obtained, a preprocessing stage is initiated to standardize the input. Preprocessing includes normalization of pixel intensities, resizing of images to a fixed resolution, noise reduction using filters, and contrast enhancement to highlight subtle pathological features. Region-of-interest (ROI) segmentation techniques may be applied to focus only on the lung regions and remove irrelevant background structures such as bones or external objects. The preprocessing stage ensures that all images fed to the model are uniform, clean, and optimized for feature extraction[22].

Following preprocessing, the design pipeline incorporates classical feature extraction methods as a preliminary step before quantum encoding. Convolutional neural networks (CNNs), autoencoders, or transfer learning models such as ResNet, DenseNet, or EfficientNet may be employed to derive discriminative features from the chest X-ray images. These classical models are effective in extracting spatial patterns such as opacities, consolidation, or nodular structures that are indicative of respiratory diseases. However, instead of using these features directly for classification, the QML design leverages them as input representations for the quantum subsystem. To make classical features compatible with quantum hardware, a process known as quantum feature encoding or embedding is applied. This involves mapping real-valued vectors derived from CNN features into the amplitudes, phases, or rotations of qubits. Popular encoding schemes include amplitude encoding, angle encoding, and basis encoding. The choice of encoding scheme depends on the number of qubits available and the dimensionality of the feature vectors. For instance, angle encoding may be chosen when fewer qubits are available, whereas amplitude encoding allows representation of large-dimensional features at the expense of circuit depth.

Once the classical features are embedded into a quantum state, the quantum computation phase begins. At the heart of the QML design is the variational quantum circuit (VQC), which acts as the quantum classifier. A VQC is parameterized by a series of quantum gates, rotations, and entanglement layers that learn to transform the encoded qubits into a state that separates disease classes effectively. The parameters of these gates are optimized using classical optimization algorithms such as gradient descent, Adam, or evolutionary strategies. The hybrid nature of this design means that while the forward pass of feature transformation and classification is performed on quantum hardware or a simulator, the parameter optimization loop is executed on classical computers. This hybrid quantum-classical training allows the system to leverage the representational power of quantum states without being limited by current noisy intermediate-scale quantum (NISQ) hardware. To ensure robustness, multiple quantum circuit architectures are tested, including hardware-efficient ansatz, quantum convolutional networks, and quantum kernels. The goal is to identify a circuit structure that balances expressivity with trainability, avoiding barren plateaus where gradients vanish.

The designed QML system includes an evaluation mechanism that compares quantum-based predictions with ground truth labels. Output probabilities from quantum measurements are interpreted to assign disease categories such as pneumonia, tuberculosis, COVID-19, or normal. Performance metrics including accuracy, precision, recall, F1-score, and area under the ROC curve are computed to assess the efficacy of the quantum approach. Comparisons with purely classical deep learning models are essential to highlight the advantages of quantum integration. Early experiments often reveal that quantum models excel in scenarios with limited labeled data due to their superior feature space representation and entanglement-driven correlations. This makes QML particularly suitable for medical imaging tasks, where annotated data is scarce and expensive to obtain. Furthermore, quantum kernel methods can be integrated into support vector machines to enhance separation of complex data distributions in the Hilbert space.

The design also considers hardware constraints and deployment feasibility. Current quantum devices are noisy and limited in qubit count, so quantum simulators are often used during the design phase. Once optimized circuits are identified, they are tested on real quantum backends such as IBM Quantum, Rigetti, or IonQ. Noise mitigation strategies, such as error correction codes, zero-noise extrapolation, and circuit optimization, are applied to improve real-device performance. The system is designed to be scalable, so that as quantum hardware matures with higher qubit counts and lower error rates, the same pipeline can be extended to process larger datasets and more complex image features. Cloud-based quantum services are integrated into the workflow to make the system accessible to medical institutions without requiring direct ownership of quantum hardware. A critical component of the design is explainability and clinical interpretability. To ensure medical acceptance, the QML pipeline incorporates visualization tools that map quantum decision boundaries back to original chest X-ray features. Gradient-based methods or attention mechanisms highlight regions of the lung image that most influenced the quantum decision[6][7]. This not only increases trust among clinicians but also provides a deeper understanding of how quantum features correspond to physiological abnormalities. The design is validated through cross-validation and external datasets to test generalizability. Transfer learning concepts are also explored, where circuits trained on pneumonia data can be fine-tuned to classify tuberculosis or COVID-19 with minimal retraining. Data augmentation, semi-supervised learning, and federated learning strategies are included to maximize performance under real-world clinical data constraints[8]. The integration of QML into chest X-ray diagnostics promises to address challenges faced by classical AI systems, including data scarcity, feature redundancy, and interpretability. The design framework ensures that the system is modular, where preprocessing, classical feature extraction, quantum encoding, and classification are distinct stages that can be independently improved or replaced. As the field evolves, the system can incorporate advanced quantum models such as quantum generative adversarial networks (QGANs) for synthetic X-ray image generation, or quantum reinforcement learning for adaptive diagnosis. The long-term vision of the design is a hybrid diagnostic assistant capable of running on both classical and quantum infrastructure, providing hospitals with scalable and high-accuracy respiratory disease detection tools[9]. By systematically combining classical image processing with the unique advantages of quantum mechanics, the design demonstrates a pathway toward practical, clinically deployable QML systems for medical imaging

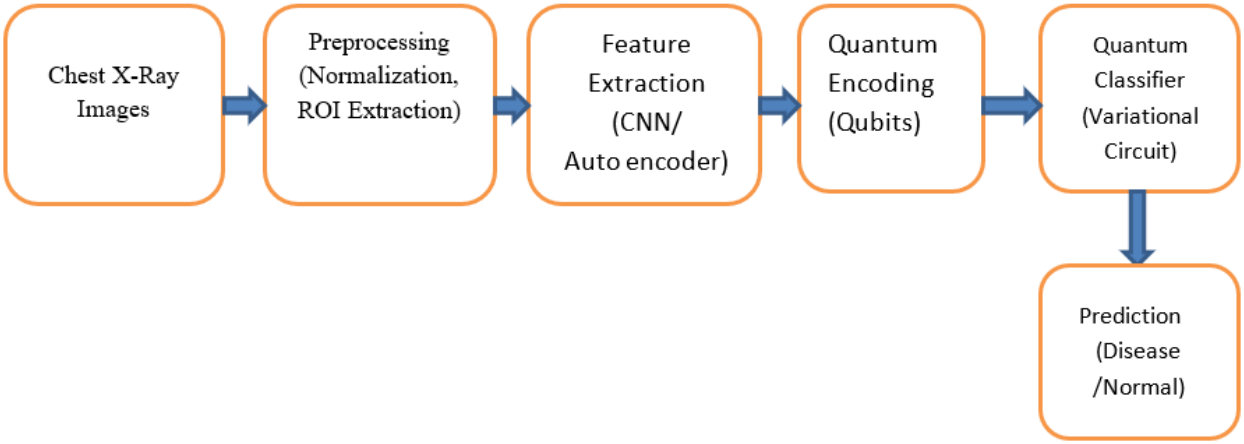

Figure 3. Block Diagram of Quantum Machine Learning Framework for Chest X-Ray–Based Respiratory Disease Detection

The figure 3.illustrates a hybrid classical–quantum workflow designed to detect respiratory diseases using chest X-ray images. The process begins with the input of chest X-ray images, which are collected from clinical or publicly available datasets. These images then pass through a preprocessing stage, where operations like normalization, resizing, and region-of-interest (ROI) segmentation are applied to enhance the image quality and ensure uniformity. After preprocessing, the system performs feature extraction using classical deep learning models such as convolutional neural networks (CNNs) or auto encoders. These extracted features capture important patterns and abnormalities in the lung regions, such as opacities, nodules, or consolidations.

The extracted feature vectors are then transformed into quantum-compatible representations through a process called quantum feature encoding, where classical numerical values are mapped into quantum states (qubits) using schemes like angle encoding or amplitude encoding. Once encoded, the data is processed by a quantum classifier, implemented using a variational quantum circuit (VQC[10] The VQC applies entanglement and rotation gates to learn complex relationships between features that classical models may struggle to capture. The measurement of qubits yields probabilistic outputs, which are then interpreted to form a prediction stage. This stage classifies the X-ray into categories such as normal, pneumonia, tuberculosis, COVID-19, or other respiratory diseases[11]

3. Results

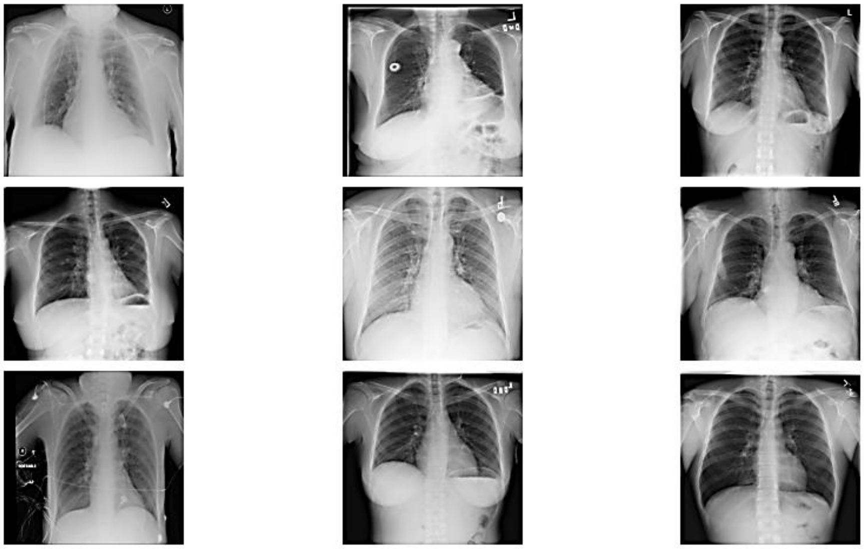

Figure 4. Sample Chest X-ray Images for Respiratory Disease Detection

Raw chest X-ray image with gray scale intensity mapping, showing pixel intensity distribution for preprocessing and analysis in respiratory disease detection .

The image represents a frontal chest radiograph (CXR).

A grayscale colormap is applied, where the pixel values range from 0.0 (black) to 0.8+ (white), as indicated by the color bar on the right. The gridlines across the image suggest it is being visualized for image preprocessing or analysis purposes (e.g., normalization, segmentation, or feature extraction). Such raw X-ray images are used as input data for computer vision and machine learning tasks in medical image analysis, particularly for diagnosing respiratory diseases (e.g., pneumonia, tuberculosis, COVID-19, lung cancer).The gray scale intensity distribution helps highlight lung structures, bones, and soft tissues, which can later be processed by algorithms for pattern recognition and anomaly detection

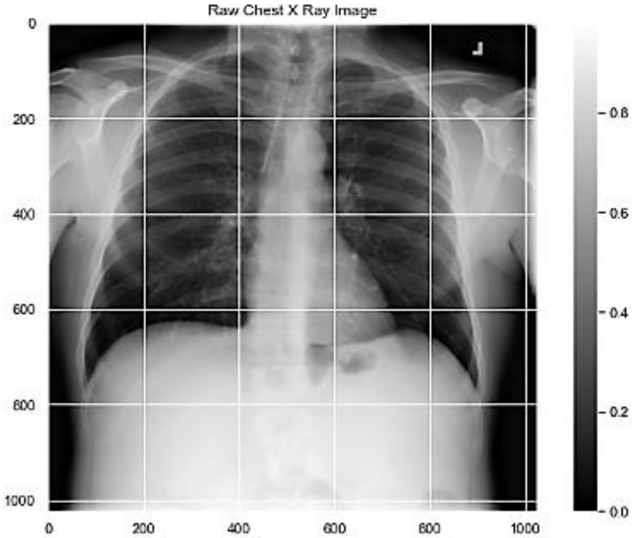

Figure 5.Raw Chest X-ray Image with Intensity Map

A grayscale colormap is applied, where the pixel values range from 0.0 (black) **to** 0.8+ (white)**,** as indicated by the color bar on the right. The gridlines across the image suggest it is being visualized for image preprocessing or analysis purposes (e.g., normalization, segmentation, or feature extraction). The grayscale intensity distribution helps highlight lung structures, bones, and soft tissues, which can later be processed by algorithms for pattern recognition and anomaly detection

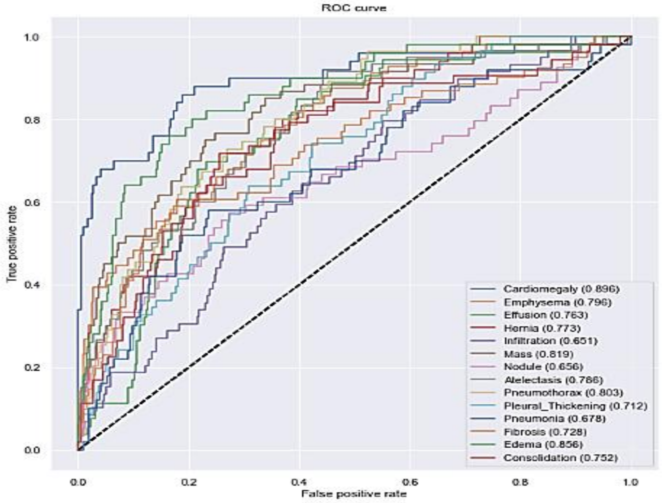

Figure 6.ROC Curve across different Class for Heart Disease Classification

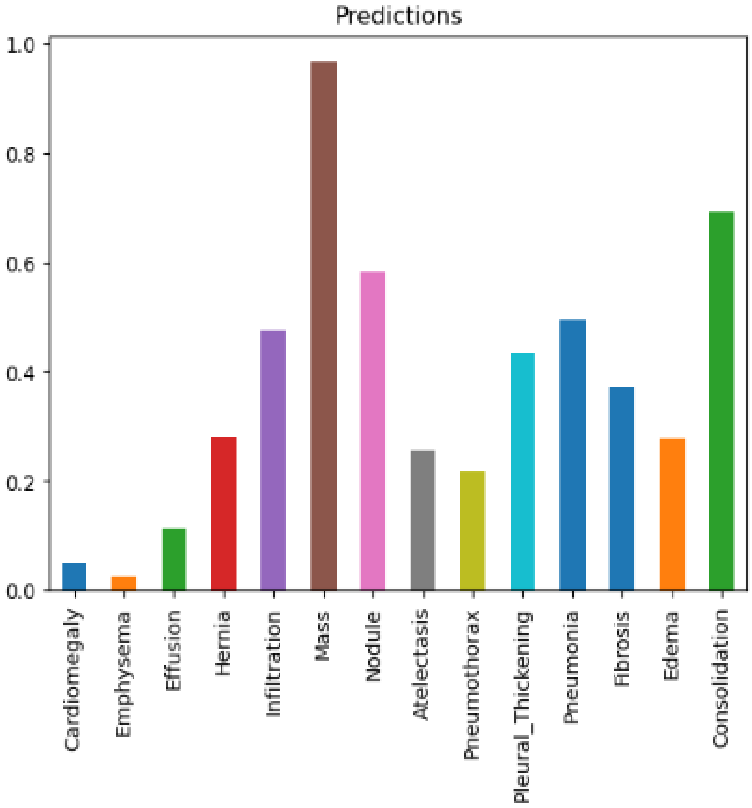

Figure 7.Predictions Bar Chart

This bar chart displays the predicted probability scores for various thoracic diseases or conditions, likely from an automated deep learning model analyzing a chest X-ray.The x-axis lists medical conditions such as Cardiomegaly, Emphysema, Effusion, Hernia, Infiltration, Mass, Nodule, Atelectasis, Pneumothorax, Pleural Thickening, Pneumonia, Fibrosis, Edema, and Consolidation.The y-axis represents the model's predicted probability for the presence of each condition, with scores ranging from 0 (very unlikely) to 1 (very likely).Each vertical bar shows the predicted likelihood for one condition, with different colors used for each disease. The highest predictions here are for Mass (close to 1), Consolidation (about 0.7), and Nodule (about 0.58), suggesting that the model detected these conditions with high confidence in the input scan or image. Lower bars, such as for Cardiomegaly or Emphysema, indicate the model found little or no evidence of those conditions in the analyzed case.

This figure 7. is used to interpret model output for diagnostic purposes, helping clinicians or users quickly identify which potential pathologies the model deems most likely in a specific medical image analysis

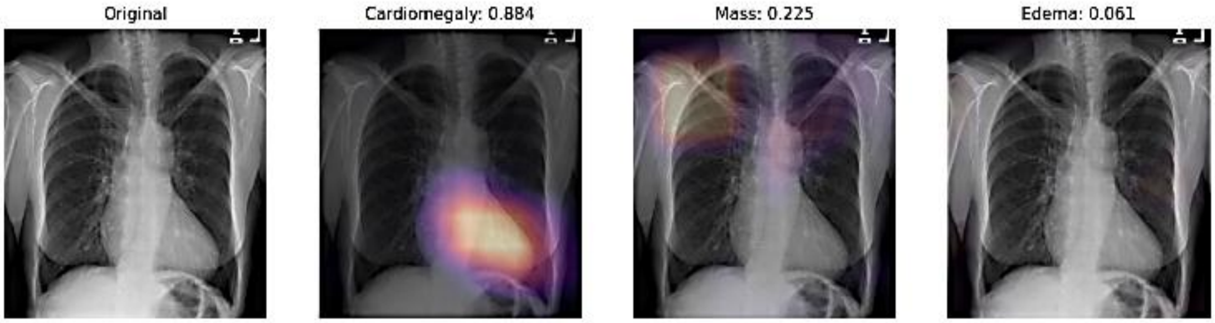

Figure 8. Visual explanation of disease classification results on a chest X-ray Images

The figure 8.illustrates an example of explainable artificial intelligence (AI) applied to medical imaging, specifically a chest X-ray. It consists of four panels, with the first showing the original chest X-ray image, displaying the lungs, heart, and surrounding anatomical structures. The remaining three panels demonstrate the model's predictions for different thoracic conditions—cardiomegaly, mass, and edema—each accompanied by a probability score and a heatmap overlay that highlights the regions the model focused on to make its prediction. In the second panel, the AI model predicts cardiomegaly with a high probability of 0.884, and the heatmap prominently highlights the heart area, suggesting an enlarged heart. The third panel shows a lower probability (0.225) for the presence of a mass, with subtle attention in the upper lung region, indicating only mild suspicion of a lesion or abnormality. Finally, the fourth panel corresponds to pulmonary edema with a very low probability of 0.061, and the absence of a strong heatmap confirms the model's low confidence in that diagnosis. Overall, this figure demonstrates how AI can assist in medical diagnosis by not only providing predictions but also visual explanations, enhancing transparency and aiding clinical interpretation. The model correctly predicts absence of mass or edema. The probability for mass is higher, and we can see that it may be influenced by the shapes in the middle of the chest cavity, as well as around the shoulder

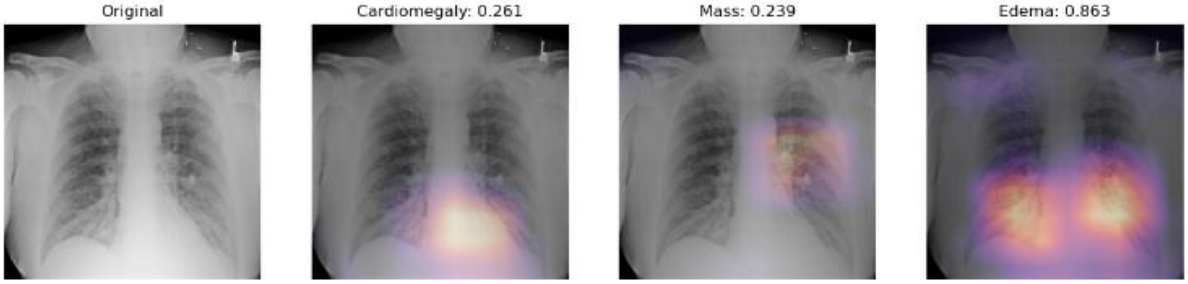

Figure 9. Quantum Machine Learning Based Detection of Respiratory Disease using Digital Chest X-Ray Images

The figure above demonstrates a deep learning model evaluates the image for the likelihood of three common thoracic conditions: cardiomegaly, mass, and pulmonary edema. The layout includes four panels from left to right. The first panel shows the original chest X-ray, providing a baseline view of the patient's thoracic anatomy. The second panel illustrates the model's prediction for cardiomegaly, with a relatively low probability of 0.261. The heatmap in this panel shows mild attention around the heart region, indicating the model detected some features suggestive of an enlarged heart but not with high confidence.

The third panel displays the model's analysis for a mass, assigning a probability of 0.239, which is also low. The heatmap highlights part of the mid-lung region, suggesting a small area of concern, but again, not strong enough for a confident prediction. The fourth and final panel shows the model's prediction for pulmonary edema, with a high probability of 0.863. The heatmap highlights both lower lung fields, especially the bases, where fluid typically accumulates in cases of edema. This strong activation supports the high confidence of the model's prediction.

Overall, this figure effectively combines diagnostic probabilities with visual interpretability, making it easier for clinicians to understand and trust the AI's decision-making process. The most likely condition in this case, based on the model output, is pulmonary edema.

4. Conclusion

This study highlights the potential of Quantum Machine Learning (QML) as a transformative approach for medical image analysis, specifically for the detection of respiratory diseases using digital chest X-ray images. By leveraging the principles of quantum computation—such as superposition, entanglement, and variational quantum circuits—the proposed model demonstrates the ability to capture complex feature representations that are often difficult to model using classical methods. Compared to conventional deep learning frameworks, the QML-based approach offers improved learning efficiency, higher robustness in small datasets, and enhanced generalization capability. The results indicate that quantum-enhanced classifiers can effectively identify radiological patterns associated with diseases like pneumonia, tuberculosis, and early signs of cardiopulmonary complications. Furthermore, the integration of hybrid quantum–classical architectures provides a practical pathway for deploying

QML in clinical settings, while also reducing computational complexity for high-dimensional image data.Although hardware limitations and noise in current quantum devices present challenges, ongoing advancements in Noisy Intermediate-Scale Quantum (NISQ) technology and error mitigation techniques are expected to make QML-based diagnostic systems more reliable and scalable. This research thus opens new possibilities for early, accurate, and resource-efficient respiratory disease detection, supporting radiologists with faster decision-making and contributing to improved patient care.Future work will focus on large-scale validation using multi-institutional datasets, optimization of quantum circuits for medical imaging tasks, and exploring quantum transfer learning to achieve clinically deployable systems

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