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Quantum-Enhanced AI System for Chest Disease Detection from Medical Reports and X-ray Images

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ABSTRACT:

The growing need for intelligent healthcare systems has resulted in the use of AI systems for efficient and precise disease diagnosis. But most of the diagnostic systems available today consider only medical reports or only chest x-ray images. This can have an adverse impact on the efficiency of the diagnostic results and the clinical decision-making process. In order to overcome these problems, this project presents a Hybrid Quantum AI Framework for Disease Diagnosis Using Medical Reports and Chest X-ray Images, combining Machine Learning (ML), Deep Learning (DL), and Quantum Machine Learning (QML) into one healthcare system. In the proposed system, users can upload their medical reports and chest x-ray images using a web-based application. For processing medical reports, OCR and NLP technologies will be used, whereas chest x-ray images will be processed using CNNs. The disease classification is done by applying quantum machine learning models such as Quantum Support Vector Machines or Variational Quantum Classifiers through Qiskit and PennyLane on the fused features. It also assesses the performance of both quantum and classical machine learning models and makes a comparison between them to identify their efficiency. Lastly, it outputs the predicted disease name, confidence score, and a diagnosis summary that can be easily understood by healthcare professionals. This framework is capable of utilizing the power of hybrid quantum-classical intelligence for computer-aided diagnosis systems.

Keywords: *Variational Quantum Classifier, Quantum Neural Network, Optical Character Recognition (OCR), Natural Language Processing (NLP), Convolutional Neural Networks (CNN).*

1.Introduction:

Nowadays, Artificial Intelligence is becoming a useful tool in healthcare, especially for helping students and people in rural areas understand their medical reports and X-ray images and gain a better understanding of their possible health conditions. Medical information can sometimes be difficult for a normal person to understand because reports contain medical terms and X-ray images require proper knowledge to interpret. Our project focuses on using AI to make this information easier to understand and provide an initial indication of possible chest-related conditions. Our project, "Quantum-Enhanced AI System for Chest Disease Detection from Medical Reports and X-ray Images," is designed to analyze two different types of medical information: text-based medical reports and chest X-ray images. Instead of depending on only one source, our system combines information from both sources to make the prediction more comprehensive. When a user uploads a medical report, the system first extracts the information from the document using Optical Character Recognition (OCR). This is useful when the report is available as a scanned document or image. After extracting the text, Natural Language Processing (NLP) techniques are used to identify important medical terms, observations, symptoms, and findings from the report. At the same time, the user can upload a chest X-ray image. The image is preprocessed and passed through a Convolutional Neural Network (CNN). The CNN learns important visual features from the X-ray, such as patterns or abnormalities that may be associated with different chest diseases.The next important step is to bring the information from these two sources together. The features obtained from the medical report and chest X-ray are combined using feature fusion. This allows the system to consider both the textual information and visual information while making the prediction.For example, information mentioned in a report can provide additional context to the patterns detected in the X-ray. The unique aspect of our project is the integration of Quantum Machine Learning (QML) with classical AI techniques. We explore approaches such as Quantum Neural Networks (QNN), Variational Quantum Circuits (VQC), and hybrid quantum-classical models for classification. Since current quantum computers have limitations such as noise, limited qubits, and computational constraints, a hybrid approach allows us to make use of both classical and quantum techniques. The system then generates the final result in a simple and understandable form. It can provide the predicted chest disease, confidence score, and a brief summary of the result. This makes the output easier for users to understand instead of presenting only technical model predictions. The main purpose of this project is not to replace doctors or provide a final medical diagnosis. Rather, it is intended to act as an AI-based supporting and awareness tool. It can help users understand what their medical report and X-ray may indicate and can also assist healthcare professionals by bringing information from multiple sources into one system. Overall, our project combines OCR, NLP, CNN, multimodal feature fusion, and Quantum Machine Learning into a single framework. Through this combination, we aim to develop a more intelligent and user-friendly system for chest disease detection from medical reports and X-ray images, while also exploring the potential of quantum computing in healthcare.

2.Literature Survey:

Pal, De, and Hazra present a survey of quantum machine learning applications in medical image analysis. The study reviews different quantum and hybrid quantum-classical approaches, including Quantum Neural Networks (QNN), Quantum Convolutional Neural Networks (QCNN), Quantum Support Vector Machines (QSVM), and Variational Quantum Classifiers (VQC). It examines quantum circuit architectures, data encoding methods, quantum gates, and circuit configurations used for medical image classification. The survey highlights the potential of quantum machine learning for healthcare applications and identifies important research directions. However, limited qubits, quantum noise, small datasets, and insufficient validation on real quantum hardware remain major challenges [1]. A comprehensive study investigates the application of quantum machine learning in medical image analysis, covering areas such as MRI, CT scans, X-ray images, and histopathology. The study explores quantum models, including VQC, QCNN, QNN, and hybrid quantum-classical approaches, for applications such as disease diagnosis, image segmentation, reconstruction, and surgery planning. It examines how quantum computing can be integrated with classical artificial intelligence to support medical image processing. The study highlights the potential of quantum techniques for improving medical image analysis and supporting healthcare decision-making. However, quantum noise, data encoding complexity, scalability, interpretability, and hardware limitations remain important challenges [2]. Prabha and Kumaran investigate the performance of quantum-enhanced medical X-ray image processing using hybrid quantum algorithms. The study explores the integration of classical image-processing techniques with quantum methods to improve medical X-ray image enhancement. Approaches involving Quantum Fourier Transform (QFT), Variational Quantum Circuits (VQC), and hybrid quantum processing are considered for analyzing and enhancing medical images. The work focuses on comparing classical, quantum-inspired, and hybrid quantum approaches using image-quality measures. However, limited dataset availability, quantum noise, and the computational constraints of current quantum systems may affect practical implementation [3]. Mallek and colleagues propose a free-energy-driven quantum-enhanced framework for pneumonia triage using chest X-ray images. The approach combines deep-learning-based latent feature representation with quantum feature transformation to support pneumonia classification. Monte Carlo dropout is used to estimate prediction uncertainty, helping assess the reliability of the model's outputs. The study explores how quantum processing can be integrated with classical deep-learning features for medical image analysis and decision support. However, the use of a small, low-resolution dataset, binary classification, and simulated quantum components limits the conclusions that can be drawn about broader clinical applications [4]. Alfajri and colleagues investigate hybrid quantum-classical convolutional neural networks for multiclass lung X-ray image classification. The approach combines classical convolutional neural networks with quantum machine-learning components to classify chest X-ray images into categories such as normal, lung opacity, and viral pneumonia. Different quantum-gate configurations are investigated to understand their influence on classification performance. The study explores the potential of integrating quantum computing with classical deep learning for automated lung disease recognition. However, the limited dataset size and scalability constraints of current quantum hardware remain important challenges for practical medical diagnosis [5]. Shirin and colleagues present a systematic review of quantum computing applications in medical diagnostics and treatment. The study examines quantum machine learning approaches for medical imaging and healthcare, along with applications in genomics, drug discovery, healthcare security, and clinical decision support. It reviews different quantum algorithms and discusses their potential roles in improving healthcare-related computational tasks. The review highlights emerging opportunities for integrating quantum computing into medical diagnosis and treatment. However, current quantum technologies face challenges related to noisy intermediate-scale quantum (NISQ) hardware, limited qubits, data encoding, scalability, and the lack of sufficient clinical validation [6]. Balasubramani and colleagues propose a quantum-enhanced artificial neural network model for efficient medical image compression. The approach combines quantum feature extraction and classical neural-network techniques to reduce the storage requirements of medical images while attempting to preserve important image information. The study considers medical imaging applications involving MRI, CT, and X-ray data and evaluates image quality and compression performance. It explores the potential of quantum-enhanced learning for improving medical image storage and processing efficiency. However, quantum hardware limitations, noise, and computational complexity remain challenges for practical deployment [7]. Gupta and colleagues conduct a systematic review of quantum machine learning applications in digital health. The study investigates whether quantum machine-learning methods can outperform classical machine-learning approaches in healthcare applications. It examines different techniques, including quantum neural networks, quantum kernels, and quantum support vector machines, while considering their performance under realistic operating conditions. The review highlights the importance of reliable experimental comparisons when evaluating quantum approaches for digital health. However, limited evidence of practical quantum advantage, hardware noise, scalability issues, and data encoding challenges remain significant barriers to real-world adoption [8].

Cid and colleagues develop and validate open-source deep neural networks for comprehensive chest X-ray interpretation through a retrospective, multicentre study. The approach uses deep-learning models to identify multiple abnormalities in chest X-ray images and aims to support automated radiological analysis. It also considers the use of natural language processing to extract information from radiology reports, connecting image interpretation with clinical text. The study demonstrates the importance of large-scale evaluation and open-source deep-learning systems for chest X-ray analysis. However, differences in datasets, reporting practices, disease labels, and clinical settings can affect the generalization of the models to new healthcare environments [9]. Chan and colleagues investigate hybrid quantum transfer learning for long-tailed chest X-ray classification. The approach uses pre-trained deep-learning models to extract image features and integrates quantum machine-learning components for classifying chest X-ray abnormalities. It focuses on long-tailed and imbalanced datasets, where some disease categories contain considerably fewer examples than others. The study explores the potential of combining transfer learning and quantum classification to improve medical image analysis under class-imbalance conditions. However, limited quantum hardware resources, the complexity of quantum feature encoding, and the difficulty of handling rare disease categories remain important challenges [10]. Asadoorian and colleagues investigate a pre-trained quantum convolutional neural network for COVID-19 disease classification using computed tomography images. The approach explores quantum transfer learning to reuse learned image representations and apply quantum processing to medical image classification. The study focuses on distinguishing COVID-19 cases from non-COVID-19 cases using CT images. It contributes to research on integrating quantum neural networks with medical image analysis and evaluating their potential for disease recognition. However, the focus on a specific disease and imaging modality, together with quantum hardware and scalability limitations, restricts the direct application of the approach to broader medical diagnosis tasks [11]. Houssein and colleagues propose a hybrid quantum-classical convolutional

neural network for COVID-19 prediction using chest X-ray images. The approach combines classical convolutional neural networks for image feature extraction with quantum circuits for further feature processing and classification. It investigates the use of hybrid quantum-classical architectures for both binary and multiclass COVID-19 classification. The study demonstrates a research direction for integrating quantum computing with deep learning for chest X-ray-based disease recognition. However, the scalability of quantum circuits, computational costs, and the limitations of current quantum hardware present challenges for practical deployment [12]. Mathur and colleagues investigate medical image classification using Quantum Neural Networks. The study explores quantum models for classifying medical images, including retinal fundus images and chest X-rays, and compares their performance with classical neural-network approaches. It considers the use of quantum simulators and real quantum hardware to evaluate the feasibility of quantum-based image classification. The work contributes to understanding how quantum neural networks can be applied to healthcare-related image recognition tasks. However, the limited number of qubits, circuit-training difficulties, hardware noise, and the need for further evaluation on larger datasets remain important challenges [13]. Kiani, Villanyi, and Lloyd investigate quantum algorithms for medical imaging. The study explores quantum approaches for medical image reconstruction, particularly in modalities such as MRI, CT, and PET. It examines the computational complexity of quantum reconstruction methods and compares their potential with conventional classical approaches. The work highlights possible applications of quantum algorithms in processing and reconstructing medical images. However, practical implementation depends on efficient data loading, suitable quantum hardware, and the ability to demonstrate computational advantages over classical methods under realistic conditions [14]. Cohen, Bertin, and Frappier develop Chester, a web-delivered system for locally computed chest X-ray disease prediction. The system uses deep-learning techniques to analyze chest X-ray images and provide predictions that can support medical professionals as a second-opinion tool. It focuses on making automated chest X-ray analysis accessible through a web-based application while allowing local processing. The work demonstrates the usefulness of integrating deep-learning-based medical image classification into an accessible software system. However, the system primarily focuses on chest X-ray images and does not combine report-text analysis, multimodal feature fusion, and quantum classification within a single framework [15].

3.Methodology:

3.1 Frame work:

The proposed framework is designed for automated chest disease detection using medical reports, chest X-ray images, and hybrid quantum-classical machine learning. Medical reports and chest X-ray images are provided as inputs to the system and processed using appropriate techniques to identify disease-related information. The framework supports report-based disease detection, chest X-ray-based disease detection, and multimodal disease detection when both inputs are available.

The system uses EasyOCR for extracting text from scanned medical reports and ResNet-50 for extracting visual features from chest X-ray images. The extracted features are combined through feature fusion when both modalities are provided. Principal Component Analysis (PCA) is then applied to reduce the dimensionality of the feature representation before quantum processing. A Variational Quantum Classifier (VQC) is used for disease classification, with RY rotation gates considered for quantum data encoding. The system aims to provide a predicted disease class and an associated confidence score to support medical decision-making.

3.2 Medical Report and Image Processing:

Medical reports and chest X-ray images are analyzed to obtain useful information related to disease identification. Preprocessing is performed to prepare the inputs for the corresponding models. For scanned medical reports, EasyOCR is used to detect and recognize text from report images, converting the extracted information into machine-readable text. The resulting text is processed into a suitable feature representation for classification.

For chest X-ray images, preprocessing prepares the images for ResNet-50. The network extracts visual features associated with patterns that may be relevant to chest diseases. These extracted features are used in subsequent classification stages. When both a medical report and a chest X-ray are provided, the extracted text and image features are combined to support multimodal disease detection. Appropriate preprocessing is important because variations in image quality, document format, and input characteristics may affect the quality of the extracted features.

3.3 Model Implementation:

EasyOCR: EasyOCR is used to extract text from scanned or image-based medical reports. It identifies text regions and recognizes characters and words, converting report images into machine-readable information. The extracted text provides the input for report-based disease analysis.

ResNet-50: ResNet-50 is used for chest X-ray image analysis and visual feature extraction. Its residual connections help train a deep convolutional neural network by allowing information to pass through the network more effectively. The extracted image features are used for chest disease classification.

Principal Component Analysis (PCA): PCA is used to reduce the dimensionality of the extracted feature vectors. It identifies principal components that capture important patterns in the data and represents the features using a smaller number of dimensions. This step helps reduce the complexity of the feature representation before quantum processing.

Variational Quantum Classifier (VQC): VQC is used as the quantum machine-learning classification component. The reduced features are encoded into quantum states using RY rotation gates. A parameterized quantum circuit processes the encoded states, and measurement results are used to obtain classification outputs. During training, a classical optimizer adjusts the circuit parameters to improve classification performance.

3.4 Feature Fusion and Classification:

The proposed system supports three input configurations: medical report only, chest X-ray only, and combined medical report and chest X-ray inputs. For report-only diagnosis, features are obtained using EasyOCR and the report-processing stage. For X-ray-only diagnosis, visual features are extracted using ResNet-50. When both inputs are available, the extracted text and image features are combined through feature fusion. PCA is applied to the resulting feature representation to reduce dimensionality before the VQC classification stage. The VQC then processes the encoded features and generates outputs for the relevant disease classes.

The system is designed to investigate the suitability of combining classical feature extraction with quantum classification. Different model configurations and classical baseline classifiers can be evaluated to compare performance. The effectiveness of the proposed approach is determined through experimental results rather than assuming that quantum classification will always outperform classical methods.

3.5 Confidence Score and Prediction Output:

The proposed system is designed to provide a predicted disease class along with a confidence score. The classification output is obtained from the trained model, and the score is derived from the model's outputs using a defined probability-mapping method. For the VQC, measurement outcomes must be converted into suitable class scores or probabilities. The resulting values can be used to identify the predicted class and estimate the model's confidence, provided the probability mapping is appropriately defined and validated. The objective is to make the prediction output easier to interpret by presenting the predicted disease category and its associated score. The confidence score represents the model's estimated certainty and should not be interpreted as a confirmed medical diagnosis. The system is intended to support healthcare professionals rather than replace clinical assessment.

3.6 Multimodel Diesese Detection:

The proposed framework extends disease identification beyond the analysis of a single input type by supporting both medical reports and chest X-ray images. Report-based analysis uses extracted text to identify relevant medical information, while X-ray-based analysis uses visual features obtained through ResNet-50.When both inputs are available, feature fusion combines information from the two modalities before dimensionality reduction and classification. This allows the system to consider information from medical documentation and image-based observations within a unified prediction pipeline.The framework therefore supports individual and combined-input diagnosis. Its effectiveness depends on the quality and relevance of the input data, the feature extraction process, and the model's ability to generalize to unseen medical cases.

3.7 Quantum Computing Model:

The project incorporates quantum machine learning through the Variational Quantum Classifier. Unlike a separate exploratory quantum module, the proposed VQC is intended to participate directly in the classification pipeline after feature extraction, feature fusion where applicable, and PCA. The reduced classical features are encoded into quantum states using RY rotation gates. The quantum circuit applies trainable operations and may include entangling gates, depending on the implemented architecture. Measurement produces classical outputs that are used for classification, while a classical optimizer updates the trainable parameters during model training. The quantum component is used to investigate the potential of hybrid quantum-classical learning for chest disease classification. The project can compare the VQC with classical baselines to examine predictive performance and computational requirements. Practical constraints include limited qubit availability, circuit noise, measurement variability, and the computational cost of training.

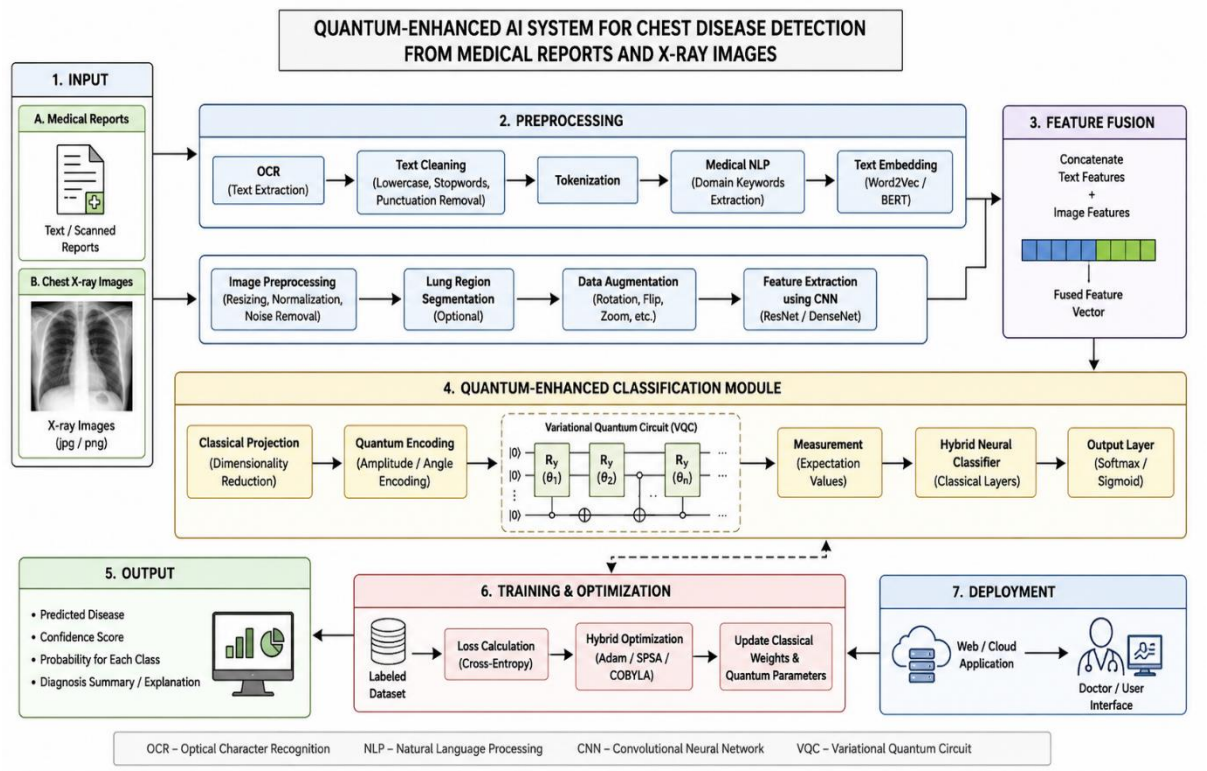
3.8 Model Evaluation and Comparision:

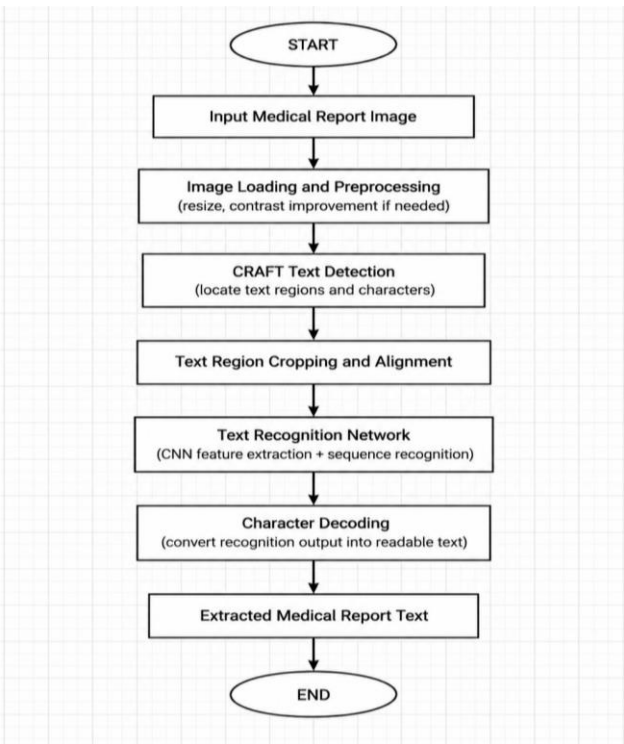
The proposed framework requires evaluation to determine its suitability for medical disease classification. The models are assessed using appropriate performance measures, such as accuracy, precision, recall, F1-score, and a confusion matrix, depending on the classification task and available dataset. The VQC can be compared with suitable classical classification methods to evaluate whether the quantum-based approach offers any practical benefit. Evaluation should use separate training, validation, and test data to reduce the risk of misleading results. For multimodal diagnosis, the combined-input configuration can also be compared with report-only and X-ray-only configurations. This helps determine whether integrating information from both modalities improves disease classification. The final conclusions are based on experimental evidence rather than assumed improvements.

3.9 Web-Based Application and Prediction Delivery:

The proposed system is intended to provide an interface through which users can upload a medical report, a chest X-ray image, or both inputs. The uploaded data are processed by the corresponding components, and the resulting features are passed through the classification pipeline. The system returns the predicted disease category and its associated confidence score, where supported by the implemented model. For combined inputs, the prediction is generated using the fused feature representation. The objective is to make the proposed hybrid AI framework accessible through a web-based application and demonstrate the integration of OCR, deep learning, dimensionality reduction, and quantum classification in a single workflow. Any generated predictions are intended for research and decision-support purposes and require appropriate validation before clinical use.

Fig.2: Flow chart





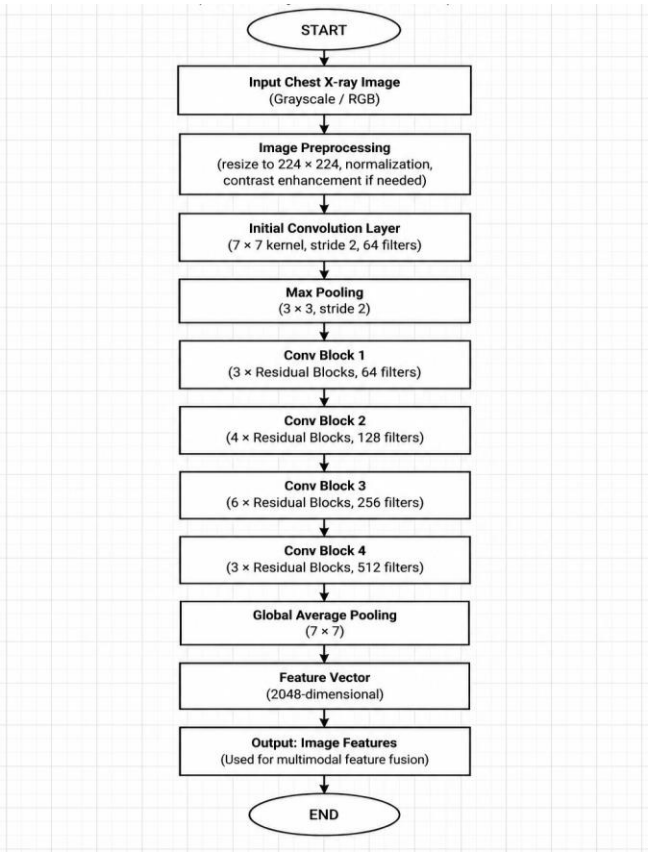


Fig.3: Flowchart of EasyOCR **Fig.4: Flowchart of ResNet-50**

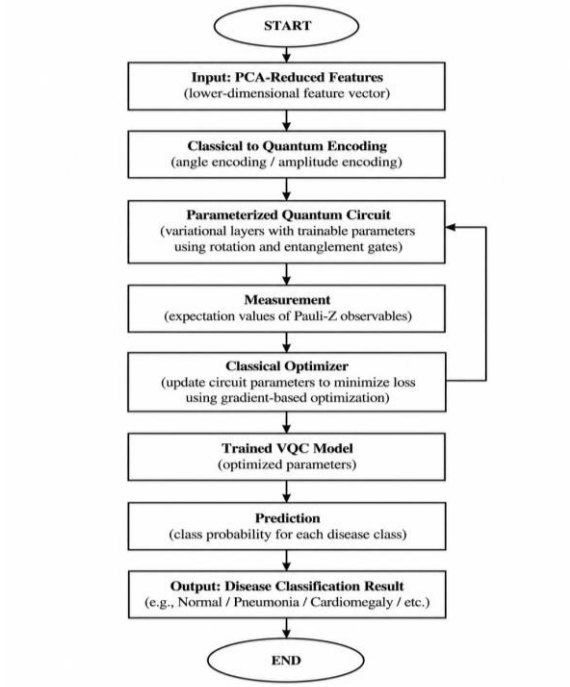


Fig.5: Flowchart of VQC

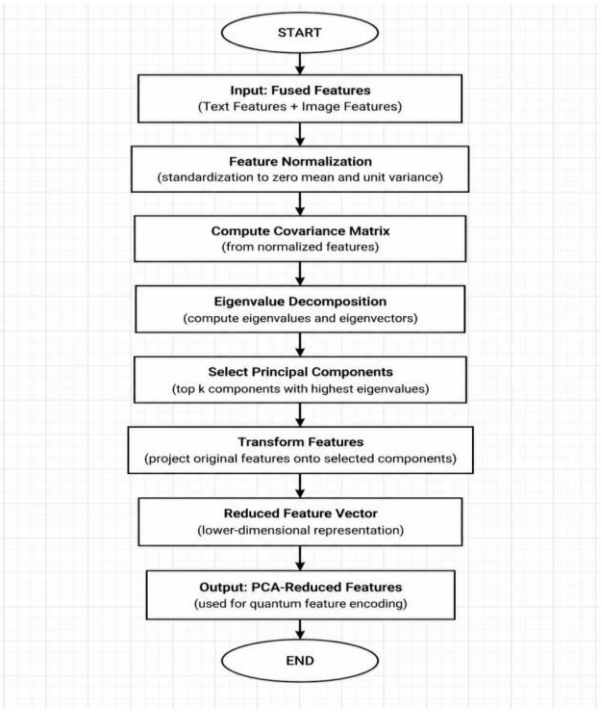


Fig.6: Flowchart of PCA

Benchmark Models:
Implements ResNet-50 and suitable classical machine learning classifiers as benchmark models to compare their performance against the proposed hybrid quantum AI framework. The comparison helps validate the effectiveness of the proposed EasyOCR, PCA, and Variational Quantum Classifier (VQC) approach in detecting chest diseases using medical reports and chest X-ray images.

Results:

PCA Logistic Regression Model: Achieved an ROC-AUC of 83.11%, with a precision of 78.20%, recall of 79.30%, and F1-score of 81.70%, showing balanced classification performance.

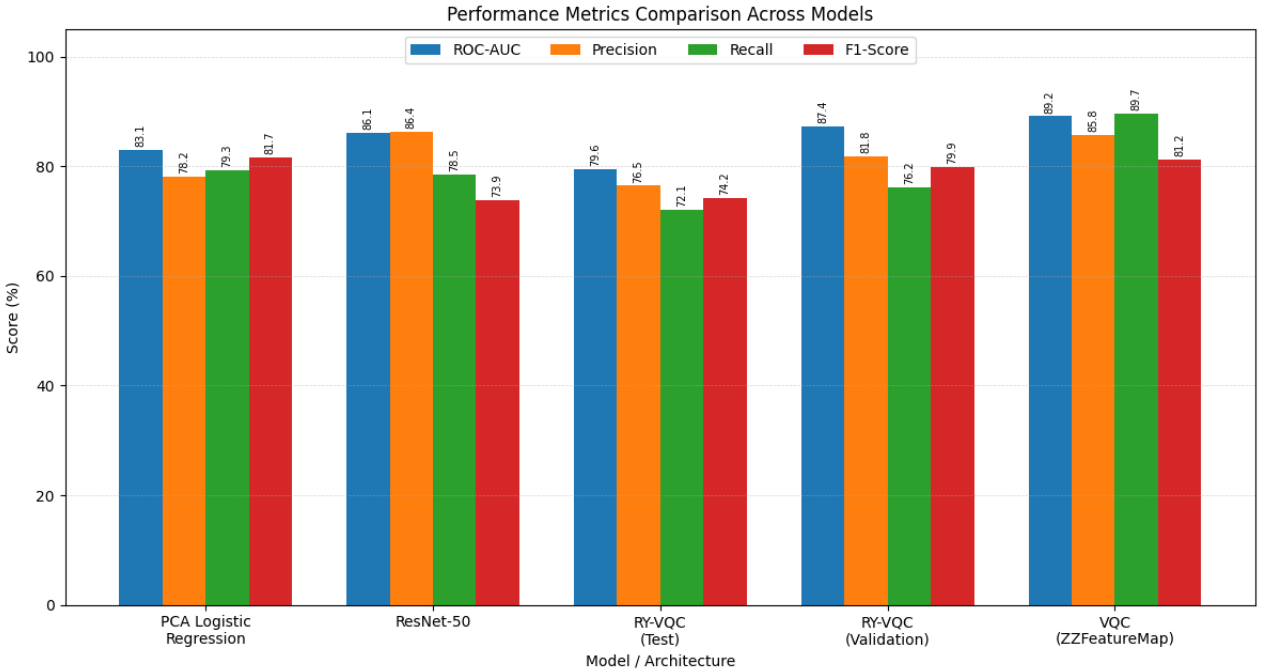
ResNet-50 Model: Recorded an ROC-AUC of 86.10% and the highest precision of 86.40% among the compared models, demonstrating its ability to identify important chest X-ray features.

RY-VQC – Test Model: Achieved an ROC-AUC of 79.60%, with a precision of 76.50%, recall of 72.10%, and F1-score of 74.24% on the test data.

RY-VQC – Validation Model: Achieved an ROC-AUC of 87.40%, with a precision of 81.80%, recall of 76.20%, and F1-score of 79.93%, showing improved performance during validation.

VQC – ZZFeatureMap Baseline: Achieved the highest ROC-AUC of 89.17% and recall of 89.70%, with a precision of 85.80% and F1-score of 81.25%, demonstrating the strongest overall ROC-AUC performance among the compared models.

Fig.7: Model Performance Comparison



Comparision and Discussion:

Ref No	Objectives	Limitations	Advantages	Gaps
[4]	Develop a quantum-enhanced framework for pneumonia detection from chest X-ray images by combining deep-learning features with quantum processing and uncertainty estimation.	Focuses mainly on pneumonia detection; performance depends on the quality of the input data and quantum-classical processing.	Combines deep-learning feature extraction with quantum feature transformation and considers prediction uncertainty.	Further research is needed to integrate medical-report text with X-ray images and evaluate the framework across multiple disease categories.
[5]	Develop a hybrid quantum-classical convolutional neural network for multiclass lung X-ray classification and investigate different quantum-gate configurations.	Focuses on chest X-ray images; quantum circuit complexity and computational resources may limit scalability.	Integrates classical CNNs with quantum computing for medical image classification.	Medical-report analysis, OCR-based text extraction, PCA-based dimensionality reduction,and multimodal feature fusion can be explored in a unified framework.
[9]	Develop and validate an open-source deep-learning system for comprehensive chest X-ray interpretation and detection of multiple abnormalities..	Focuses primarily on chest X-ray interpretation and requires careful validation across different clinical settings.	Supports automated detection of multiple chest X-ray abnormalities and provides a foundation for AI-assisted radiology.	Integration with quantum classification and automated extraction of information from scanned medical reports requires further investigation.
[10]	Develop a hybrid quantum transfer-learning framework for chest X-ray classification, particularly for datasets with imbalanced disease categories.	Class imbalance and the computational requirements of quantum processing may affect performance and scalability.	Combines pretrained feature extraction with quantum machine learning and investigates classification of long-tailed chest X-ray data.	A unified system combining report-based features, ResNet-50 image features, PCA, and VQC needs further evaluation
[13]	Investigate quantum neural networks for medical image classification and compare quantum approaches with classical neural networks using medical image datasets.	Evaluation may be constrained by dataset size, feature dimensionality, limited qubits, and quantum hardware noise.	Provides a basis for evaluating quantum neural networks on medical imaging tasks and comparing them with classical approaches.	A practical multimodal pipeline integrating EasyOCR, ResNet-50, PCA, and VQC, with systematic classical-model comparisons, remains an important area to investigate.

Conclusion:

Early and accurate disease detection is important for improving medical diagnosis and supporting effective healthcare decision-making. The proposed project develops a hybrid quantum-classical AI framework for disease detection using medical reports and chest X-ray images. EasyOCR is used to extract text from scanned medical reports, while ResNet-50 extracts important visual features from chest X-ray images. Principal Component Analysis (PCA) reduces the dimensionality of the extracted features, and the Variational Quantum Classifier (VQC), using RY rotation gates for quantum data encoding, is proposed for disease classification.

The framework supports report-based diagnosis, X-ray-based diagnosis, and multimodal diagnosis by combining information from both inputs. It aims to provide a predicted disease category and an associated confidence score to support the interpretation of results. Classical machine learning models are also considered as benchmarks to compare their performance with the proposed quantum classifier. Overall, the project aims to provide an integrated and intelligent approach to medical disease detection by combining OCR, deep learning, dimensionality reduction, and quantum machine learning for healthcare decision support. The effectiveness of the framework will be assessed through experimental evaluation, and its predictions are intended to assist healthcare professionals rather than replace clinical diagnosis.

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