Early Detection of Coronary Heart Disease Using Hybrid Quantum Machine Learning Approach

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Abstract

Coronary heart disease (CHD) is a severe cardiac disease, and hence, its early diagnosis is essential as it improves treatment results and saves money on medical care. The prevailing development of quantum computing and machine learning (ML) technologies may bring practical improvement to the performance of CHD diagnosis. Quantum machine learning (QML) is receiving tremendous interest in various disciplines due to its higher performance and capabilities. A quantum leap in the healthcare industry will increase processing power and optimise multiple models. Techniques for QML have the potential to forecast cardiac disease and help in early detection. To predict the risk of coronary heart disease, a hybrid approach utilizing an ensemble machine learning model based on QML classifiers is presented in this paper. Our approach, with its unique ability to address multidimensional healthcare data, reassures the method's robustness by fusing quantum and classical ML algorithms in a multi-step inferential framework. The marked rise in heart disease and death rates impacts worldwide human health and the global economy. Reducing cardiac morbidity and mortality requires early detection of heart disease. In this research, a hybrid approach utilizes techniques with quantum computing capabilities to tackle complex problems that are not amenable to conventional machine learning algorithms and to minimize computational expenses. The proposed method has been developed in the Raspberry Pi 5 Graphics Processing Unit (GPU) platform and tested on a broad dataset that integrates clinical and imaging data from patients suffering from CHD and healthy controls. Compared to classical machine learning models, the accuracy, sensitivity, F1 score, and specificity of the proposed hybrid QML model used with CHD are manifold higher.

Keywords: Healthcare 4.0, Heart Disease, Deep Learning, GPU, Quantum Machine Learning, Quantum neural networks, Quantum Bits, Quantum Annealing,

1. Introduction

Quantum computing and machine learning are two rapidly evolving fields that, when combined, can transform healthcare, particularly in early cardiac disease prediction. The

Healthcare 4.0 brought about a shift in lifestyle that contributed to the development of heart-related diseases such as diabetes, high cholesterol, obesity, and physical inactivity. Heart disease was the cause of 18 million deaths in 2017, and by 2050, it is expected to account for almost 58 million fatalities [1]. An international concern is the rising frequency of cardiac deaths; according to WHO, 85% of cardiovascular patients reside in low or middle-income nations, and cardiovascular disorders account for 52% of deaths in wealthy nations [2]. Furthermore, it raises the chance of Alzheimer's disease, dementia, COVID-18, and cognitive dysfunction [3,4,5,6]. Early identification lowers the risk of these diseases, dramatically saves the heart disease-related death rate, and enhances the health budget. As a result, in recent decades, early diagnosis of cardiovascular illnesses has been a significant research challenge.

Early detection of coronary heart disease can significantly improve prognosis by enabling earlier intervention and management, which can reduce the risk of severe outcomes such as heart attacks and heart failure. S.P. Patro et al. [7] designed a heart disease prediction framework using five machine learning models with UCI Machine Repository. Hossain et al. [8] propose a hybrid convolutional neural network (CNN) and long short-term memory (LSTM) deep learning model to identify cardiovascular diseases (CVD) from clinical data combined with feature engineering and explainable AI. Traditional diagnostic methods for CHD, such as stress tests, angiography, and blood tests, have sensitivity, specificity, and cost limitations. More accurate, reliable, and cost-effective tools are needed to enhance early detection and diagnosis. However, traditional ML and deep learning (DL) models for predicting heart disease often need help handling imbalanced datasets. Farah Mohammad et al. [9] developed a continuous wavelet transformation and CNN-based hybrid model for Heart Disease Prediction. Their WT-CNN uses RUSBoost-based data balancing and achieves an exceptional accuracy of 97.2% in predicting heart disease.

S V Babu et al. [10] proposed a QuEML model for predicting heart diseases using the Kaggle data repository, which performed well in accuracy and computational time. Hybrid QML combines classical machine learning techniques with quantum computing to uncover patterns in data that traditional approaches might miss. This could lead to more precise and early detection methods for CHD. Quantum-enhanced machine learning is vital in sustaining patient-oriented attention to healthcare patrons. Yogesh Kumar et al. [11] presented a QML model of its significance in heart failure detection on a dataset of 14 attributes. They verified that QRF, QKNN, QDT, and QGNB are better than traditional ML algorithms in heart failure detection.

Hybrid QML techniques could enhance the ability to accurately predict individual risk profiles, allowing for more personalized and effective management strategies. On the other hand, traditional machine learning methods frequently have significant calculation times and little processing power. Quantum machine learning techniques have been created to address these deficiencies. Superposition and entanglement, two quantum mechanics concepts, are the foundation upon which the QML algorithms are built. An algorithm may assess many positions' impacts on the system response at once by considering the superposition characteristic. As a result, it dramatically reduces computing time. According to the entanglement characteristic, two particles are connected even when they are very far apart. As a result, QML algorithms are appropriate for large-scale or complicated issues and can significantly reduce computing time. This research suggests a hybrid approach using random forests and quantum neural networks to address the problem. Despite the widespread usage of QML algorithms and the critical relevance of early coronary artery disease prediction, only some methods currently employ QML algorithms for cardiovascular disease prediction. The proposed QML architecture is shown in Figure 1.

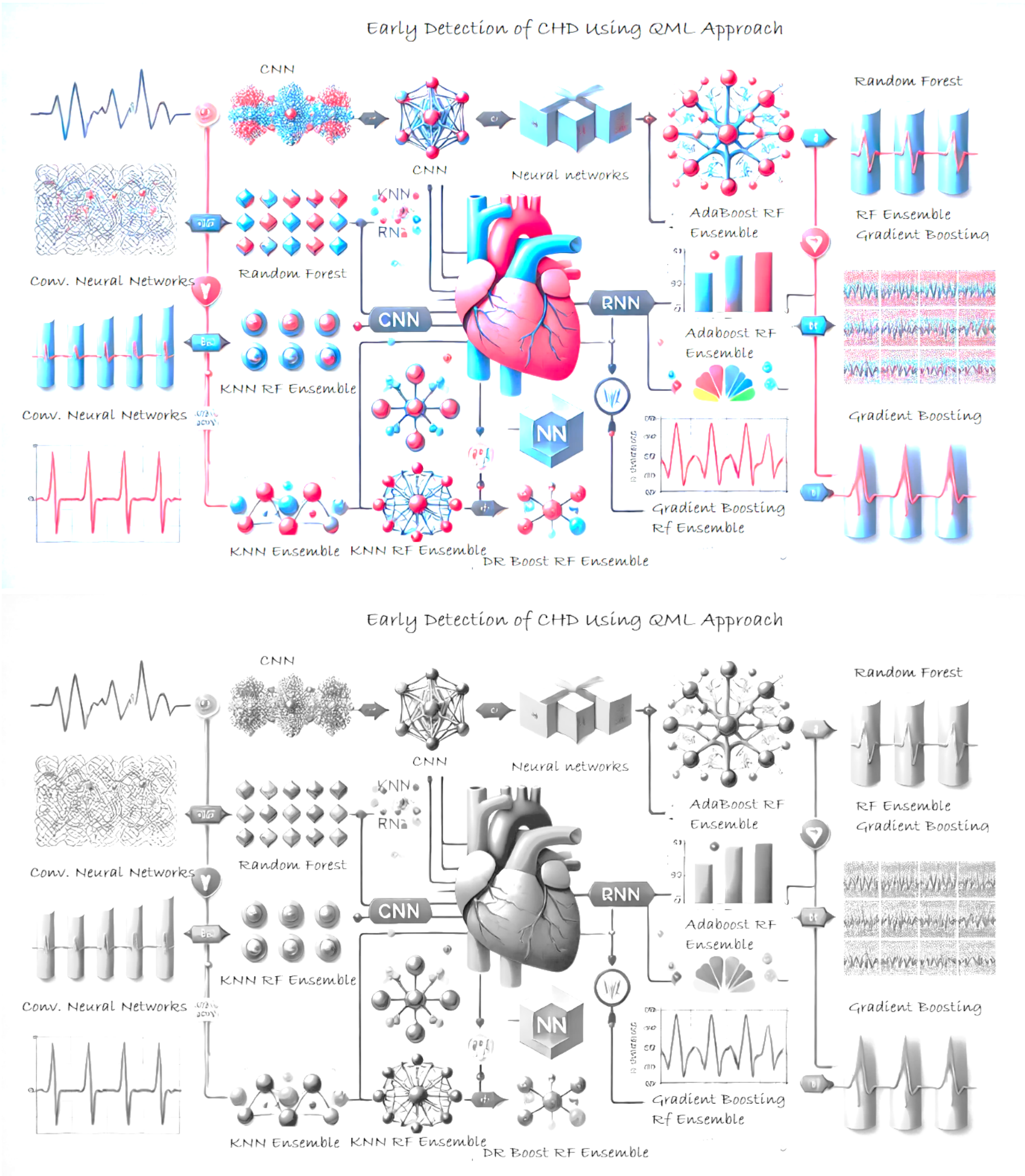


Figure 1. The proposed architecture of Early Detection of Coronary Heart Disease Using a Hybrid Quantum Machine Learning Approach.

Figure 1 shows a hybrid and multi-model approach for detecting coronary heart disease using classical ML techniques, including CNN, RNN, Random Forest, KNN, and ensemble learning-based techniques such as Adaboost and Gradient Boosting. A quantum machine learning integration will significantly enhance computational efficiency and accuracy while operating with large and complex biomedical data, such as ECG signals. Electrocardiogram signals are the main feed of data in the CHD detection process and are fed to several machine-learning models. Convolutional Neural Networks form one of the most typically used types for time series data like ECG. It can learn patterns, local structures, and anomalies from time-series data of heart rhythms effectively. Adding several layers of CNNs sequentially, the ou puts are processed through other machine learning models such as Random Forest and KNN RF Ensembles. Further, the data is passed from CNN into the neural networks for further feature extraction and classification. The neural networks analyze complex nonlinear relationships of features that may signal early appearances of coronary heart disease. Similarly, K-Nearest Neighbors and Random Forest ensembles were utilized for pattern analysis and to provide predictive insights based on patient data similarities. Ensembles combine many different models to give better performance with predictability and robustness than one single model alone. Adaboost RF Ensemble uses an Adaptive Boosting algorithm that focuses on improving the performance of weak classifiers by giving special attention to misclassified cases. It becomes the most potent ensemble for enhancing predictive accuracy with random forest and gradient boosting. Similar to other ensemble methods used to optimize the performance of the model, gradient boosting improves the model's ability to make better predictions by taking care of previous iteration errors. Further, these boosting techniques will refine the predictive results developed by the earlier models. The final prediction of these two models would be one, which would correspond to either a high or low risk for coronary heart disease of the patient. After several processing layers, these output results bring together the best merits of different models: CNN, RNN, Random Forest, KNN, Adaboost, and Gradient Boosting. It may be applied in areas not explicitly drawn, whereby quantum machine learning models are being brought forward to enhance the speed of computation and the performance of the models. The system utilizes time-series and feature-based classification techniques to ensure a strong early detection mechanism concerning coronary heart disease.

Key Components of the Model:

1. **Quantum Computing**:
    - **Quantum Bits (Qubits)**: Unlike classical bits, qubits can exist in multiple states simultaneously, enabling quantum computers to process vast amounts of data much faster.
    - **Quantum Algorithms**: Algorithms like Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNN), and Quantum K-Means can handle complex computations more efficiently than their classical counterparts.
    - **Quantum Annealing**: Useful for optimization problems, which are common in machine learning, especially in the training of models.
2. **Hybrid Machine Learning**:
    - **Classical Machine Learning**: Techniques like decision trees, logistic regression, and classical neural networks are well-understood and can be integrated into the hybrid model.

  - **Quantum-Classical Integration**: Combining quantum algorithms with classical machine learning methods can enhance the model's performance. For example, using a quantum processor to optimize the weights in a classical neural network.
3. **Data Integration and Pre-processing**:
  - **Big Data Analytics**: Handling and processing vast amounts of patient data, including electronic health records (EHRs), medical imaging, and genetic information.
  - **IoT Devices**: Incorporating data from wearable devices and sensors that monitor patients.

2. Literature Review

Most of the recent research uses a classic machine learning-based approach toward the early detection of coronary heart disease. This paper provides an overview and analysis of the machine learning classifiers used to diagnose chronic diseases, followed by their implementation and assessment. It illustrates the value of machine learning classifiers in the healthcare industry and how they can produce more accurate predictions. Decision trees, SVMs, random forests, and artificial neural networks are widely used, which are trained on data that includes patients' demographics, past medical history, and test results [12,13,14]. Olawade et al. [15] and Burton et al. [16] illustrated the efficacy of deep learning algorithms for predicting coronary artery disease using echocardiography data while managing high accuracy related to non-invasive diagnostics. Researchers also use random forests and logistic regression models to estimate CHD based on risk factors such as blood pressure, cholesterol level, diabetes and other lifestyle parameters [17,18,19]. Most of them target feature selection methods indirectly to enhance the quality of a prediction with the most minor computational complexity. Since medical datasets are ever-increasing in their dimensionality and complexity, inefficiency regarding computation and interpretation by classical algorithms encourages exploration into quantum enhancement methodologies.

Quantum computing has superior computational abilities and is fast gaining centre stage in machine learning; thus, it has a potential for using machine learning for intricate, high-dimensional data analyses. The quantum computer uses qubits, similar to the bits in classical computers, in that they can solve complicated problems and exchange information [20,21]. A few research works have started looking at applications of QML in health diagnostics, early cancer detection, and heart-related ailments. According to Sengupta et al. [22], quantum algorithms may significantly speed up the classification tasks related to medical diagnostics. Theoretically, QML outperforms classical algorithms in handling complex and multi-variable interactions from a large dataset, improving accuracy and model speed in disease prediction [23,24]. However, despite such potential, practical applications of pure QML in the healthcare domain remain in their infancy due to the present-day hardware limitations of quantum computers. The resultant development in this respect involves formulating hybrid quantum-classical machine learning models that would try to fill the gap between classical ML methodologies and quantum computing powers. Classical models are employed to perform feature extraction and pre-processing, whereas, for cases where computational tasks like optimization and large-scale pattern recognition need to be performed, quantum algorithms take over.

Recent work has shown that such hybrid methods can be even more computationally efficient and accurate than both classical models purely and their pure quantum counterparts [25,26]. Suzuki et al. [27] examine QML models based on quantum support vector classification (QSVC) and regression (QSVR) using a quantum circuit simulator. The performance of QSVC models using 4 qubits of the trapped-ion quantum computer and QSVR models on the near-term quantum device. Rui Zhang et al. [28] demonstrate a QSVM based on the regularized Newton method (RN-QSVM), which achieves an exponential speed-up over the classical algorithm. Havlíček et al. [29] proposed a quantum-enhanced feature space for SVM: quantum kernel estimation. It realized a computational speedup in classification tasks compared to classical SVM. Decoodt P et al. [30] have explored hybrid quantum-classical algorithms for applications in cardiology. Their work demonstrates how it would be possible to embed quantum algorithms in DL models for medical image analysis in an auspicious manner to detect heart diseases. A recent study by Abdulsalam et al. [31] suggests that QML classifiers outperform classical ML classifiers in heart disease prediction. Furthermore, the investigation shows that the bagging ensemble learning method raises the quantum classifiers' prediction accuracy.

The proposed hybrid QML models leveraging both quantum algorithms and the techniques of well-established classical ML can, therefore, offer more accurate and faster predictions, even in complicated and noisy medical datasets. And with ongoing improvements in quantum hardware, hybrid models are expected to further increase in medical diagnostics. While most of the classical machine learning approaches already demonstrated significant advances in CHD detection, their integration with quantum computing showed a path toward further enhancement. The practical application remains in its infancy, with the development of quantum hardware and algorithms needed to develop hybrid methods in healthcare.

3. Methodology

Development and implementation of the quantum-based hybrid ML model for early prediction of cardiac diseases amidst Healthcare 4.0 are indeed complex and multivariate, considering the involvement of sophisticated technologies and methodologies. Advanced data analytics, real-time monitoring, and personalized medicine feature prominently in this era; a lot is expected from these novel computational paradigms. Indeed, the hybrid quantum-classical machine learning model is promising in predicting early cardiac disease by exploring both quantum computing and classical algorithms. Quantum computing lies on a different framework from classical computing. Due to superposition, qubits can be in all states simultaneously, while entanglement allows quantum computers to process founts of data much easier. In machine learning, the QSVM and QNN would see that they can substantially speed up over classical alternatives, particularly when the dimension becomes exceptionally high. Logistic regression, decision trees, and neural networks are a few of the traditional ML models utilized in health care to predict various diseases, including cardiac conditions. Several of these models suffer from high-dimensional data and require increasing computational resources. Some critical limitations of these models, such as feature selection, dimensionality reduction, and optimization, can be overcome by combining quantum computing with the existing models. The authors introduce a study that merges quantum computing with classical techniques to grasp the strengths of both. The proposed hybrid model can be designed in the following sessions in the context of predicting cardiac disease.

3.1 Data Collection and Pre-Processing

The first step involves gathering data from diverse sources. Electronic health records (EHRs) provide comprehensive patient histories, demographic information, lab results, and medical imaging. Data from IoT devices, such as wearable technology, offers real-time monitoring of vital signs like heart rate, blood pressure, and ECG readings. Additionally, genomic data sheds light on genetic predispositions to cardiac diseases, while lifestyle data including information on diet, exercise, and smoking habits—further enriches the dataset. Once collected, this data undergoes rigorous pre-processing. Initial steps include data cleaning to remove inconsistencies, handle missing values, and standardize formats. Missing values can be addressed using mean/median/mode imputation, interpolation, or K-Nearest Neighbors (KNN) imputation. Outlier detection is performed using Z-Score calculations or the Interquartile Range (IQR) method to identify and manage anomalies. The data is then normalized or scaled using techniques like Min-Max Scaling, Z-Score Standardization, Robust Scaler, Logarithmic Transformation, or Box-Cox Transformation. Finally, relevant features are extracted to enhance the prediction of cardiac disease.

Z-Score: Calculate $z = \frac{X-\mu}{\sigma}$, where μ is the mean and σ is the standard deviation. Outliers are data points with |z|>threshold |z|>threshold (e.g., 3).

$$z = \frac{X-\mu}{\sigma}, \tag{1}$$

IQR (Interquartile Range): Identifies outliers by measuring the spread of the middle 50% of data. Data points outside 1.5×IQR from the first or third quartile are flagged as outliers.

$$IQR = Q3 - Q1 \tag{2}$$

Min-Max Scaling: $X' = X - Xmin \div Xmax - Xmin$ (3)

In equation 3, X' is the normalized value.

Z-Score Standardization: $X' = \frac{X-\mu}{\sigma}$ where $X - \mu$, transforms the data to have zero mean and unit variance.

$$X' = \frac{X-\mu}{\sigma} \tag{4}$$

Robust Scaler: $X' = \frac{X-\text{median}}{\text{IQR}}$, used when data contains outliers.

$$X' = \frac{X-\text{median}}{\text{IQR}} \quad \text{(v)}$$

Logarithmic Transformation: $X' = \log(X+1)$, often used to handle skewed data.

$$X' = \log(X+1) \tag{5}$$

Box-Cox Transformation:

$$X' = \frac{x^{\lambda} - 1}{\lambda}$$
$$X' = \log(X) \text{ for } \lambda = 0 \quad (6)$$

3.2 Quantum-Enhanced Machine Learning:

The model's core leverages quantum computing to enhance traditional machine learning algorithms. Quantum Support Vector Machines (QSVM) utilize quantum states to compute kernel functions that measure the similarity between data points, offering a more refined classification process. The QSVM optimization problem involves minimizing a function subject to constraints involving multipliers and data labels. Quantum neural networks (QNN) further advance this by applying unitary transformations to quantum states and optimizing parameters through quantum gradient descent or other quantum optimization techniques. The hybrid approach uses classical methods for initial data pre-processing and feature extraction while employing quantum computing for model optimization and hyperparameter tuning. The iterative training loop integrates both processors, with classical computing handling straightforward tasks and quantum computing addressing more complex ones. Model performance is evaluated using accuracy, precision, recall, and F1-score metrics.

Kernel Function: Quantum states compute a kernel function K(xi,xj) that measures similarity between data points. This can be represented as the inner product of quantum states:

$$K(xi,xj) = |\langle \phi(xi) | \phi(xj) \rangle| \quad (7)$$

Optimization Problem: The QSVM optimization problem is typically formulated as:

$$\min_{\alpha} \sum \alpha i \alpha j y i y j \, K(xi, xj) - \sum_i \alpha i \quad (8)$$

In equation 8, y_i are the labels and α_i are the multipliers.
Quantum Layers: Each layer in a QNN applies a unitary transformation $U(\theta)U(\theta)$ to a quantum state $|\psi\rangle|\psi\rangle$, parameterized by θ

$$\theta: |\psi'\rangle = U(\theta)|\psi\rangle |\psi'\rangle = U(\theta)|\psi\rangle \quad (9)$$

Loss Function: The loss function is typically the expectation value of an observable:

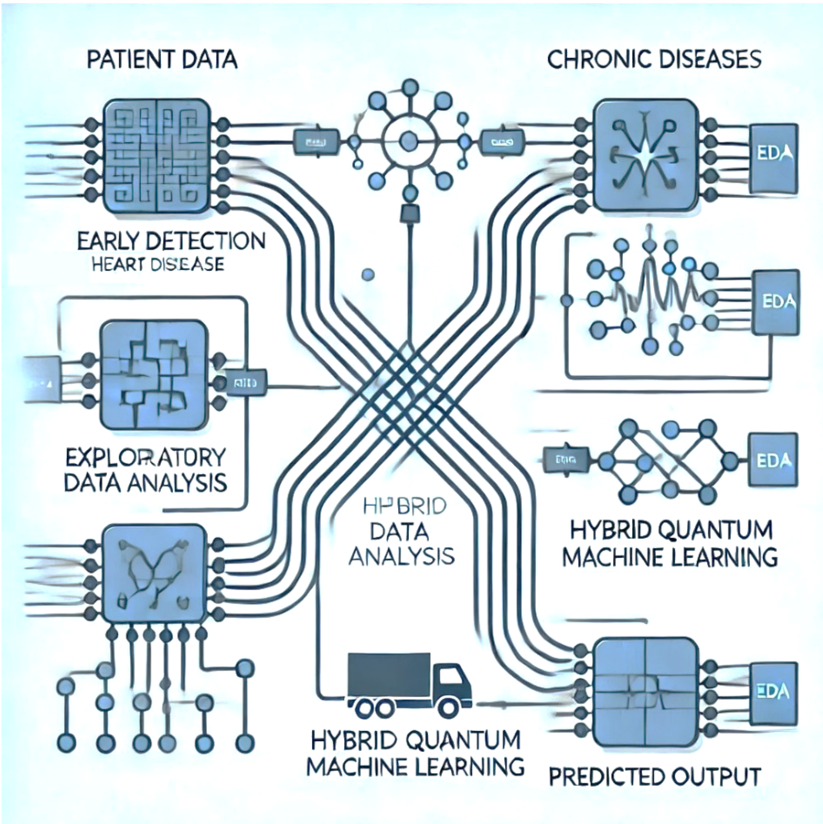
$$L(\theta) = \langle \psi'(\theta) | O | \psi'(\theta) \rangle L(\theta) = \langle \psi'(\theta) | O | \psi'(\theta) \rangle \quad (10)$$

3.3 Real-Time Prediction and Monitoring:

The model must seamlessly integrate with healthcare systems for practical application. Real-time data ingestion ensures continuous monitoring and updating of patient records from IoT devices. A predictive analytics dashboard is developed to provide healthcare providers with user-friendly visualizations of predictions and risk assessments, facilitating timely interventions and decision-making.

3.4 Implementation and Deployment:

The infrastructure setup involves utilizing a hybrid cloud environment, combining classical cloud computing resources with quantum cloud services to support the computational demands of the model. Ensuring data security is paramount, with robust measures such as encryption and access controls implemented to protect patient information. This comprehensive approach ensures the effective deployment of a quantum-based hybrid machine learning model in predicting early cardiac disease, enhancing diagnostic accuracy and patient outcomes.



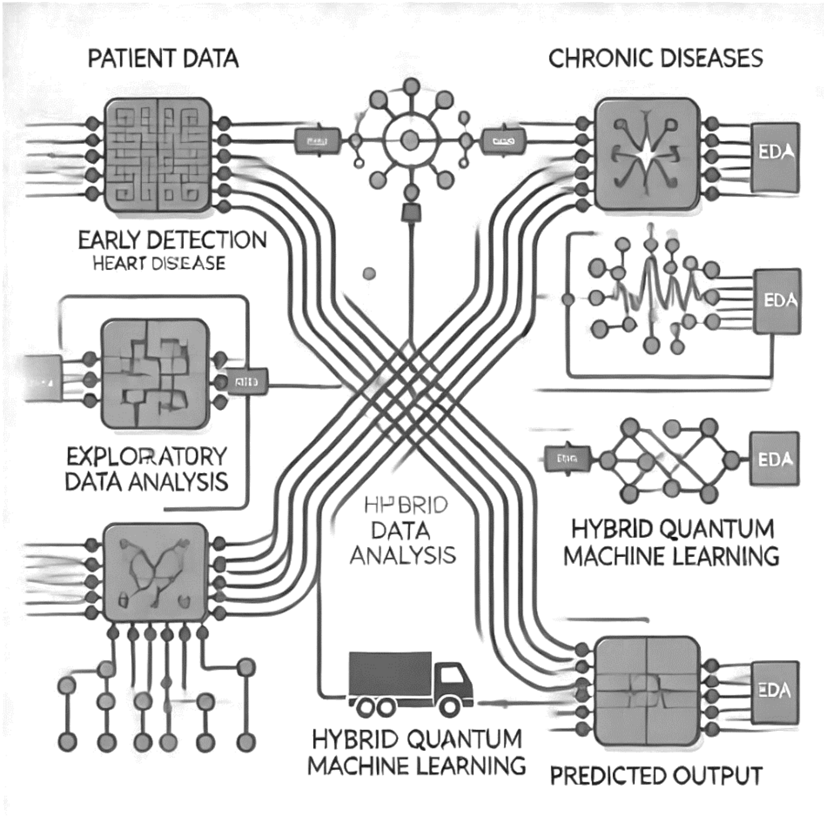


Figure 2. Block diagram of the proposed hybrid machine learning model using QML architecture.

This article provides an overview and analysis of the machine learning classifiers used in the diagnosis of chronic diseases, followed by their implementation and assessment. It then illustrates the value of machine learning classifiers in the healthcare industry and how they can produce more accurate predictions. The block diagram for the prediction model of chronic diseases is shown in Figure 2.

4. Results and Discussion

While choosing the algorithm in the domain of early prediction of cardiac disease using ML, the models' performances remain significant. Each machine learning pipeline includes performance metrics. They provide a progress indicator along with a numerical value. Metrics don't have to be differentiable to track and evaluate a model's performance during testing and training. Metrics like Accuracy, Precision, F1 Score, Recall, and Kappa are used in this study to validate the proposed method and are discussed in Tables 1 and 2.

Table 1. Performance analysis of the different classification models.

SI. No.	ML Model	Accuracy	Precision	Recall:	F1 Score	Cohens Kappa Score	Area Under Curve
1	KNN	99.99	99.99	100	99.96	99.96	1.00

2	Random Forest	99.57	99.41	99.72	99.56	99.14	0.9934
3	Linear Regression	99.99	99.99	100	99.99	99.99	0.9997
4	Decision Tree	99.97	99.96	99.97	99.91	99.94	0.9997

Table 1 below summarises important metrics of four various ML models: KNN, Random Forest, Linear Regression, and Decision Tree. Each has been evaluated for accuracy, precision, recall, F1 score, Cohen's Kappa score, and AUC.

In this hybrid approach, we take advantage of the stacking notion; a meta-classifier was paired with several classification models as an ensemble approach known as stacking. Multiple layers were arranged one after the other, with the models fulfilling their predictions in each layer. The top layer model is the base model, which informs choices by combining many models. The original data provides properties for the models in the lower layer. The model's top layer receives input from the lower levels and uses it to give a final prediction. To process the original data, the stacking approach uses numerous independent machine-learning models as input. Subsequently, the weights of each machine learning model are computed, and the input and output are predicted using the meta classifier. The algorithms with the best performance are chosen, while those with poor performance are eliminated. This method uses a meta-classifier to train many machine learning algorithms on the same dataset after combining numerous classifiers as the basis model. Table 2 shows the hybrid algorithms for cardiovascular data.

Table 2. Performance comparison of the hybrid ensemble model for Coronary heart disease detection.

SI. No.	Classification Model	Accuracy	Precision	Recall:	F1 Score
1	CNN	99.88	99.87	99.89	99.88
2	Random Forest	98.60	98.61	98.60	98.61
3	Ensemble 1	99.88	99.87	99.90	99.88
4	KNN-RF Ensemble	99.96	99.95	99.97	99.96
5	DT-RF Ensemble	99.93	99.93	99.92	99.92
6	LR-RF Ensemble	98.79	98.81	98.73	98.77
7	AdaBoost-RF Ensemble	99.93	99.94	99.92	99.93
8	Gradient Boos-RF Ensemble	98.79	98.81	98.73	98.77

The results of the various machine learning classification models in terms of their performance metrics are presented in Table 2. All these metrics are important for assessing model efficiency for detecting coronary heart disease. Of special interest is the application of hybrid quantum machine learning approaches. CNN shows quite good results in all metrics, especially with a high recall of 99.89, which means that it captures nearly all positive cases. That makes this model reliable for early detection but slightly outperforms some ensemble models. Random Forest performs solid, though it is less accurate than CNN and ensemble methods. While it has consistent performance in overall accuracy and precision, it lags. This model closely matches CNN regarding accuracy but has a higher recall at 99.90, making it marginally better in detecting true positive cases. The hybrid K-Nearest Neighbors and Random Forest) ensemble model is the strongest of all, with the highest accuracy of 99.96%, precision of 99.95%, recall of 99.97%, and F1 score of 99.96%. This seems to be the best model for early detection in this context. Another effective model is the Decision Tree and Random Forest model, which yields outstanding results on all fronts, although slightly lower than those from the KNN-RF ensemble. Its balanced performance makes it a strong candidate for consideration. The Logistic Regression and Random Forest combination in this model uses both, but its performance is not that good compared to other ensemble models.

Table 2 shows that the AdaBoost-RF Ensemble performs very well, with accuracy and precision close to the top. It is an outstanding choice, with overall performance just slightly worse than KNN-RF. Similar to the LR-RF ensemble performance, the Gradient Boost-RF Ensemble model has good performance but not as high as other ensembles. This makes it less suitable for choice. The other ensembles, LR-RF and Gradient Boost-RF, turn out only averagely and are less suitable, given that they yield lower accuracy and F1 scores. Finally, hybrid ensemble models, notably the KNN-RF Ensemble, stand out as very effective solutions for early detection of coronary heart diseases compared to solo models such as CNN and traditional Random Forest. Hybrid approaches have shown a robust and reliable solution in medical applications and offer great potential for highly accurate diagnostics.

This research develops a hybrid machine-learning prediction model for chronic diseases in such a manner to ensure that the optimum level of accuracy is ensured. It is observed that the same dataset with different ML methods has differences in their accuracy scores to make a better model. While using cross-validation for solving the overfitting problem to reach the highest accuracy by combining Decision Trees, Gradient Boosting, Gaussian Naïve Bayes, and Gradient Boosting, our primary focus will remain the selection of the best hybrid model. It would be to offer therapy to chronic disease patients which would be more effective and efficient with reduced cost. The future of quantum computing in Healthcare 4.0, driven by machine learning algorithms, will massively influence medical science and patient care because it reveals unprecedented data analysis and processing capability. While quantum technology will enable complex and voluminous health dataset manipulation with increasing efficiency, yielding more accurate and multi-faceted predictive models, its development continues. This will lead to early identification and diagnosis of a disease, personalized treatment based on the patient profile using advanced personalized medicine, and faster drug discovery by simulation of molecular interactions on an unprecedented scale. Quantum algorithms will allow data from different sources in real-time, including wearable devices, to support proactive health management and dynamic decision-making. Moreover, integrating quantum computing with machine learning will drive innovations in areas such as genomic research, whereby capabilities to model and analyze the genetic data at the quantum level will deliver insights more profoundly from mechanisms of diseases to targets for therapies. Fundamentally, the great potential for quantum computing in machine learning could set new benchmarks for successful research in medicine and patient outcomes, enhancing health care to be more predictive, personalized, and efficient in Health 4.0.

5. Conclusion

Quantum algorithms, such as quantum support vector machines and quantum neural networks, promise improved predictive accuracy by exploring extensive solution spaces and capturing intricate patterns that classical models might miss, facilitating earlier and more precise disease detection. Handling real-time data quickly supports dynamic decision-making and personalised care, enhancing patient outcomes and operational efficiency. The performance for early detection of coronary heart disease is best for the KNN-RF Ensemble and DT-RF Ensemble; KNN-RF is the best overall model, with the highest accuracy of 99.96% and a recall of 99.97%, making it very good at finding true positives with minimal false negatives, which is very important in medical diagnosis. It is also impressively performed by the AdaBoost-RF Ensemble and DT-RF Ensemble. It is only slightly worse than the KNN-RF ensemble and thus can be regarded as a feasible alternative for early detection tasks. As quantum technology advances, its integration into healthcare machine learning will drive transformative changes, unlocking new research possibilities, optimizing treatments, and setting new medical innovation and patient care standards. This research aims to develop and use a hybrid quantum machine-learning prediction model for chronic renal disease that prioritizes accuracy. To create a better model, we have examined the accuracy of the same dataset using several machine learning methods and compared their accuracy scores. This research uses cross-validation to solve the overfitting problem and achieve the highest accuracy when combining popular machine learning classifiers like decision trees, gradient boosting, Gaussian Naïve Bayes, and gradient boosting to create the best hybrid model.

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