

Design and Implement a Variational Quantum Classifier for Heart Disease Prediction

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Abstract

Heart disease is one of the major global causes of death, requiring early and precise detection for efficient treatment. With advancements in quantum computing, Variational Quantum Circuits (VQCs) have gained recognition as a valuable technique for improving learning models in medical diagnosis. This study further explores the application of VQC-based models for heart disease prediction, leveraging quantum computing to enhance classification accuracy. A hybrid quantum-classical model has been developed, which combines classical preprocessing for feature extraction from patient datasets with a VQC-based classifier for medical predictions. The quantum circuit using variational parameters is optimized to reduce the loss function and facilitate effective learning from complex medical data. This proposed approach is tested on benchmark heart disease datasets and evaluated against classical Machine Learning (ML) models, including Support Vector Machines (SVMs), Random Forests, and Neural Networks. The experimental results show that VQC-based models achieve high accuracy and outperform classical models, notably on high-dimensional, non-linearly separable data. The quantum advantage of VQCs lies in their ability to encode and process data in a huge Hilbert space. However, challenges such as noise in near-term quantum devices and scalability issues remain key. This research underscores the efficacy of VQC-based quantum machine learning in medical diagnosis, paving the way for future studies on quantum-enhanced healthcare solutions. Further advancements in quantum hardware and hybrid learning techniques could allow quantum-assisted heart disease prediction to become an effective clinical tool.

Keywords: *Medical Diagnosis, Variation Quantum Classifier, Data Pre-Processing, Feature Extraction, Heart Disease Detection.*

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1. INTRODUCTION

Heart disease is a leading cause of death worldwide; in diagnostic techniques, improving the accuracy and speed of detecting the disease is crucial. Effective treatment and better patient outcomes depend on the early detection of cardiovascular conditions, such as heart attacks, coronary artery disease, and arrhythmias, which are critical. Classical diagnostic methods include ECG, blood tests, imaging techniques, and scans. These methods are time-consuming and rely on manual interpretation, which can delay diagnosis and increase the risk of mortality. Additionally, a standard data analytics model (Figure-1(a)) was previously used and showed promising results. However, classification accuracy was lower, and complexity was high due to using multiple methods to classify a single image, including preprocessing, data preparation and normalization, feature extraction, and classification. In this case, no single

method can extract all the essential features present in the input data. The evolution of digital technologies, advancements in machine learning, and the emergence of quantum computing have led to the development of a new methodology for enhancing the diagnostic system. In medical diagnostics, rapidly evolving technologies, such as the variational quantum classifier (VQC) and quantum machine learning algorithms, have shown promise for handling high-dimensional, complex data, particularly for heart disease detection. The process of the VQC model is depicted in Figure-1(b).

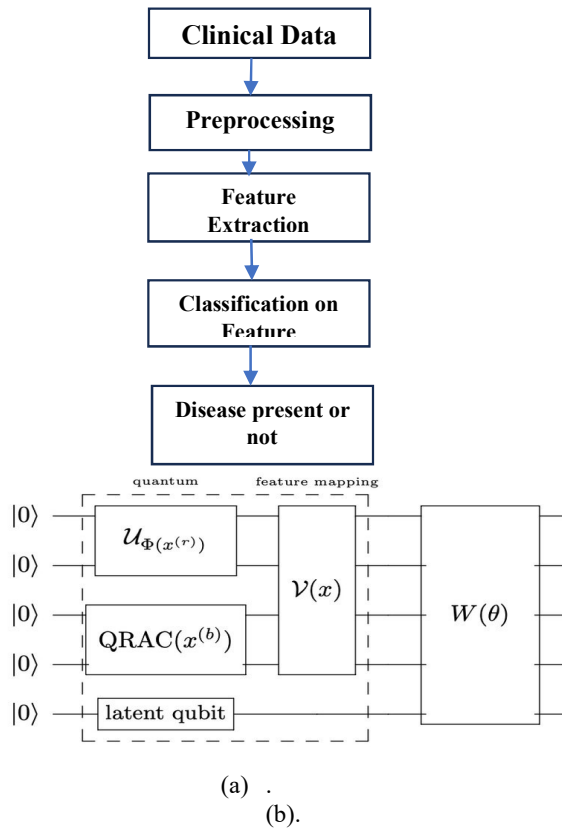


Figure-1. Existing Model

Integrating quantum computing and classical optimization techniques is known as the Variational Quantum Circuit (VQC), which is a hybrid model. The main purpose of VQC is to process data using quantum circuits that can surpass classical ML methodologies. The principles of quantum mechanics are used in VQC. Specifically, to encode data into quantum states, quantum superposition and entanglement are used, enabling algorithms to rapidly explore large solution spaces compared to traditional methods. To analyze critical and complex datasets, such as electrocardiograms, medical records, genetic data, and cardiovascular indicators, quantum methods offer significant advantages. In heart disease detection, patient data is classified using VQC into distinct categories. These categories include healthy and high-risk patients based on features such as ECG, BP, and cholesterol levels. The ability to manage large-scale, high-dimensional datasets makes VQC models more efficient and better suited than classical classifiers. VQC is particularly advantageous for handling noisy, partial, or imbalanced data, where traditional machine learning models struggle.

In the VQC model, training these complex datasets can help identify intricate patterns and relationships that classical methods may overlook, improving accuracy and enabling early detection of heart disease. Moreover, to process large volumes of

patient data, the VQC model provides stability and enables real-time clinical decision-making. Efficiency and accuracy are also improved for heart disease diagnosis. This paper explores the VQC model and its hybrid classical approach to revolutionizing heart disease diagnosis and treatment. The VQC model offers significant advantages in data processing and evaluation, surpassing classical methods. Moreover, as discussed earlier, integrating QML into healthcare poses real-time challenges, particularly regarding scalability, accuracy, and interpretability in clinical applications. In summary, quantum computing in healthcare holds great promise for enhancing accuracy, minimizing treatment delays, and saving lives by detecting cardiovascular conditions before they reach a critical stage.

1.1 Contribution of the Paper

- This paper proposes the Variational Quantum Classifier (VQC) model for detecting heart disease. It uses a quantum computing approach to deliver more accurate, efficient diagnostic results.
- The VQC model can identify complex patterns in medical datasets, thereby improving the accuracy of heart disease detection. It provides more precise results than traditional ML models.
- The quantum algorithm processes high-dimensional data more effectively, enhancing model generalization. Additionally, it does not require extensive feature engineering to process data.
- The quantum computing approach reduces inference time and accelerates training, making this model more suitable for real-time heart disease prediction.
- Quantum classifiers are more resilient to uncertainty and noisy medical datasets, yielding more reliable heart disease detection forecasts.
- Finally, by leveraging quantum-enhanced learning methods, the VQC model can detect subtle anomalies in medical datasets, enabling earlier disease detection and facilitating treatment planning tailored to the patient's heart condition.

1.3 Literature Survey

In this section, traditional research works are analyzed and discussed in detail. Both the merits and the research gaps of conventional methodologies are reviewed in detail. Schuld et al. (2019) presented an investigation into the theoretical framework for Variational Quantum Circuits (VQCs), which are primarily used for supervised learning and can generalize well to small, noisy

datasets. The efficiency of the VQC model was evaluated through numerical simulation. The results showed that it can efficiently reduce model size and outperform the traditional method. It also demonstrated that circuit-based models are highly resilient to noise, making them error-tolerant and robust. This work laid the ground for VQCs in classification, including for biomedical applications. Mari et al. (2020) have proposed a classical-quantum hybrid neural network based on the PennyLane approach. To evaluate the effectiveness and efficiency of the proposed model, it was tested using the cross-platform PennyLane library and compared with several traditional models. The experimental results indicated that the parameterized quantum circuits were effective at separating overlapping classes, as in heart disease classification tasks.

Chen et al. (2021) have presented an investigation into the effectiveness of Quantum Neural Networks (QNNs) in healthcare applications. Thus, QNN was applied to several healthcare datasets and compared against several traditional MLP models. Finally, it was observed and demonstrated that QNNs perform similarly with reduced sample sizes while being more efficient in terms of memory and training time. Li et al. (2021) have proposed an advanced Quantum Support Vector Machine (QSVM) model for early-stage cardiovascular disease prediction through classification. To evaluate the proposed model's efficiency, it was tested on various cardiovascular datasets and compared with a traditional SVM. The results showed that the proposed QSVM model achieved better generalization and non-linear separability using quantum kernels. Glick et al. (2021) presented an investigation into Variational Quantum Perceptrons, which are used to classify biomedical images and tabular data. It also indicated that QML models can extract high-level relevant features with a limited number of trainable parameters.

Rajora et al. (2022) proposed a hybrid quantum model that combines the QSVM and Logistic Regression (LR) models to predict patients' heart conditions using UCI data. The experimental results showed that the proposed hybrid quantum model effectively reduced false-positive rates and achieved 92.4% accuracy in predicting patients' heart conditions. Cerezo et al. (2021) have presented an investigation into Variational Quantum Algorithms (VQAs), which mainly focus on parameter expressibility, optimization landscapes, and training stability, which are essential factors in improving and tuning VQA models for medical predictions. Zhao et al. (2020) have applied Quantum Boltzmann Machines to high-density clinical data. It was not intended to increase the probability of heart disease. However, their

architecture shows it can learn other kinds of health-based probabilities. Yano et al. (2021) have proposed an advanced model for predicting COVID-19. It uses VQC-based binary classifiers to identify COVID-19 symptoms by analyzing patient records, demonstrating that quantum healthcare applications are being developed in the real world with limited training data. Farhi and Neven (2018) have presented the well-developed Quantum Alternating Operator Ansatz (QAOA) model for optimizing combinatorial problems. In recent years, it has been used for feature extraction in various real-time biomedical applications, thereby improving the overall performance of the QML model.

McArdle et al. (2020) presented an investigation of the QML model and highlighted its advantages and disadvantages in the life sciences, including disease prediction and drug discovery. The experimental results showed that the quantum circuits in the QML model can capture correlations in biological data, whereas the traditional model failed to do so. Abdelsalam et al. (2022) compared classical and quantum classifiers across various medical datasets to evaluate their performance. The experimental results showed that classical classifier models outperformed QML models on large datasets. In contrast, the QML model has achieved better results on smaller datasets while maintaining high scalability. Pérez-Salinas et al. (2021) have presented an investigation of various data encoding strategies for the VQC models. It was tested and trained on multiple real-time datasets to evaluate more efficient methods. The experimental results showed that the angle-encoding strategy provides more efficient results, particularly for tabular medical data, because it is easy to implement. Manzeli et al. (2023) proposed an advanced hybrid model that combines PCA and VQC to reduce data dimensionality before classification. This approach may lead to faster convergence and higher classification accuracy, indicating that the proposed hybrid model is better suited to predicting heart disease from patient ECG signals. Bharti et al. (2022) investigated Noisy Intermediate-Scale Quantum (NISQ) applications and identified heart disease prediction as a candidate use case for early quantum machine learning (QML) systems.

Together, these studies imply that Variational Quantum Classifiers and other QML models can provide a robust technique for health diagnosis, particularly when data is sparse or exhibits linear behavior. VQCs outperform the other five types of classifiers in feature efficiency, utilization of new features, and the number of training cycles required to reach the minimum error. This paper discusses three major issues: noise, interpretability, and encoding methods, and proposes a new methodology.

1.4 Limitations and Motivation

The successful use of the Quantum Machine Learning (QML) model in classifying heart disease still has several limitations that must be addressed. First, noise in quantum hardware remains a significant challenge because near-term devices are inherently noisy, affecting the performance of quantum algorithms such as the Variational Quantum Classifier (VQC). This noise makes it difficult to implement quantum circuits accurately and obtain precise results when classifying heart disease. Additionally, current quantum hardware typically has a limited number of qubits, leading VQC models to suffer from scalability issues. This limitation becomes particularly problematic when dealing with large medical datasets with numerous features. Moreover, the hybrid nature of VQC models introduces complexity, as training quantum parameters using classical algorithms is computationally intensive.

Furthermore, quantum models are susceptible to encoding classical data, and efficiently encoding structured medical data for a heart disease detector is non-trivial due to the data's dimensionality and complexity. Finally, medical data is not always clean; it may contain noise or missing values, which can negatively impact model performance. While VQC models effectively reduce dimensionality and handle noisy data, robust preprocessing strategies are essential for achieving more reliable results.

1.5 Problem Statement

Heart disease is one of the major global health issues, which requires more time and a precise diagnosis for effective treatment. Current diagnostic techniques primarily rely on traditional machine learning (ML) algorithms or manual data interpretation to identify conditions such as arterial disease, arrhythmias, and heart attacks. These approaches can lead to errors, inefficiencies, and delays. Current ML models face challenges in processing complex, high-dimensional, and noisy medical data, such as ECG patterns, cholesterol levels, blood pressure readings, and other cardiovascular indicators. These difficulties can lead to incorrect or delayed diagnosis. Conventional methods struggle with scaling data analysis, particularly in real-time clinical decision-making environments. Therefore, more effective, scalable, and precise diagnostic tools are needed to rapidly process large, complex datasets while reducing errors and improving accuracy.

Variational Quantum Classifiers (VQCs) offer a promising approach to enhancing heart disease detection by leveraging the unique properties of quantum computing, such as superposition and entanglement, to improve the diagnostic accuracy of these systems. However,

incorporating VQC into heart disease diagnostics remains largely unexplored. Concerns remain regarding the model's practical application, scalability, and ability to handle the complexities of medical datasets. Thus, the goal is to design and evaluate a Variational Quantum Classifier (VQC) that efficiently processes and classifies heart disease-related data. The aim is to outperform conventional classical machine learning models in terms of accuracy, scalability, and efficiency.

2. Proposed Model

This paper proposes a novel approach for the early prediction of heart disease. This research mainly focuses on minimizing the risk of heart disease prediction and improving model performance. During disease prediction and classification, the proposed model includes several steps: data collection, preprocessing, feature extraction, and classification. The following subsections and Figure-1 explicitly explain the performance of each step of the proposed model.

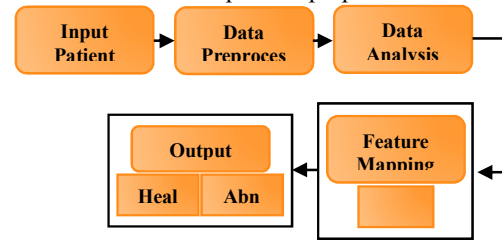


Figure-1. Workflow of The Proposed Model

2.1 Data Pre-Processing

Preprocessing is vital in training a Variational Quantum Classifier model for heart disease prediction datasets. It includes cleaning, integrating, transforming, and normalizing data to improve the model's accuracy and robustness. The steps for the model techniques and mathematical representations are discussed below.

2.2 Data Cleaning

The data cleaning process for the heart disease dataset includes handling missing values, removing duplicates, and correcting inconsistencies. Mean imputation is the common method for handling the missing value, where the mean replaces the missing value:

$$X_i^{new} = \frac{1}{N} \sum_{j=1}^N X_{ij}$$

Where the imputed value for the feature i is X_i^{new} . The number of non-missing samples is N , and j represents the observed value of feature i for a sample X_{ij} . Missing values in categorical features

are replaced with the most frequently occurring category.

2.3 Data Integration

Data integration involves combining multiple data sources into a unified dataset. If the duplication attributes are in various resources, to identify the highly related features, attribute correlation analysis is used:

$$r_{XY} = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

Where the Pearson correlation coefficient is r_{XY} , two features are X_i, Y_i and their mean values are \bar{X}, \bar{Y} . To avoid duplicates, highly correlated attributes may be merged or removed.

2.4 Data Transformations

Data transformation is the process of converting the features to make them suitable for quantum computation. The log transformation is the key transformation for highly skewed features:

$$X_i^{log} = \log(1 + X_i)$$

This minimizes the impact value. Moreover, one-hot encoding represents categorical variables as binary vectors, with each category corresponding to a binary vector. Feature scaling is another crucial transformation, particularly for quantum states, where quantum circuits require input values to be normalized within a range of $[-1,1][-1, 1][-1,1]$ for rotation-based encoding.

2.5 Data Normalization

Ensuring that all numerical features are on a similar scale prevents any single feature from dominating the quantum model. The most commonly used normalization methodology is Min-Max:

$$X_i^{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where the normalized value is X_i^{norm} and the minimum and maximum values of the features are X_{max}, X_{min} . Z-score normalization is used for standardizing features:

$$X_i^{std} = \frac{X_i - \mu}{\sigma}$$

Where the mean of the feature is μ and the standard deviation is σ .

The data is frequently scaled within the range $[0, \pi]$ $[-\pi, \pi]$ for encoding the quantum feature to ensure compatibility between classical and quantum data using the angle coding technique:

$$\theta_i = \pi \cdot X_i^{norm}$$

Where the quantum rotation angle is represented by θ_i .

2.6 Data Analysis (EDA)

Data analysis systematically collects, cleans, transforms, describes, models, and interprets data. It helps in making informed decisions by converting raw data into actionable information. Exploratory Data Analysis (EDA) is a key step in data analysis to uncover meaningful insights from raw data. It uses graphical and statistical methods to understand data structure, identify patterns, detect outliers, and explore relationships between variables. EDA uses techniques such as box plots, histograms, scatter plots, correlation matrices, and summary statistics to detect outliers, identify trends, analyze correlations, and visualize the distribution of heart disease data.

2.7 Heart Disease Prediction Using VQC Model

In machine learning, variational quantum classifiers are hybrid quantum-classical ML models that use parameterized quantum circuits (PQCs) and classical optimization to classify data. These hybrid models are applied for heart disease prediction, where the quantum feature map processes patient records for VQC. The quantum circuit also trains tunable parameters, and the presence or absence of heart disease is predicted by measuring the outcome.

2.7.1 State Preparation (Quantum Feature Encoding)

In VQC, the initial step is to encode classical data into quantum states. The input feature vector is encoded into quantum states using a feature map. The input feature vector is denoted as $x = (x_1, x_2, \dots, x_n)$.

$$|\psi(x)\rangle = U_{\phi(x)}|0\rangle^{\otimes n}$$

Where a unitary transformation that encodes the classical features into the quantum state is $U_{\phi(x)}$ and the initial ground state of n qubits is $|0\rangle^{\otimes n}$. Amplitude encoding is a standard method for normalizing classical data vectors.

$$|\psi(x)\rangle = \sum_i f_i(x) |i\rangle$$

Another method is angle encoding, where each feature map is mapped using a qubit rotation:

$$R_y(x_i) = e^{-\frac{ix_i\sigma_y}{2}}$$

Where the Pauli matrix is σ_y , this state after encoding is:

$$\left| \psi(x) \right\rangle = \bigotimes_{i=1}^n R_y(x_i) \left| 0 \right\rangle$$

There are various encoding strategies, including amplitude, angle, and basis. The most common VQC approach is angle encoding, representing each feature as a qubit's rotation. For example, the level of the patient's cholesterol is defined as x_i . We can apply a rotational gate, $R_y(\theta_i)$, where θ_i is a function of x_i . This transformation aligns the system with the input data. The patient's medical data is encoded into a unique quantum state to predict heart disease classification.

2.7.2 Model Circuit (Parameterized Quantum Circuit)

A group of parameterized quantum gates is applied to the variational models to encode the state. The model circuit is designed to learn and capture patterns in the data, a process known as the variational ansatz. In the model circuit, parameterized quantum gates are used and adjusted during training to minimize the classification loss function. The standard form of the VQC circuit is represented as:

$$U_\theta = U_L(\theta_L) \dots U_2(\theta_2)U_1(\theta_1)$$

The U_θ contains layers of quantum gates L with trained parameters

$$\theta = \theta_1, \theta_2, \dots, \theta_m.$$

The typical approaches used in rotational and entangling gates are:

$$R_y(\theta_i) = e^{-\frac{i x_i \sigma_y}{2}}$$

$$CNOT_{ij}$$

Where parameterized rotation uses $R_y(\theta_i)$ on qubit i for non-linearity and also enables the circuit to learn complex decision boundaries. The entanglement between the qubits i and j is created by $CNOT_{ij}$. After applying the U_θ , the final quantum state is:

$$\left| \psi_\theta(x) \right\rangle = U_\theta \left| \psi(x) \right\rangle$$

Finally, this model circuit can differentiate between patients with and without heart disease by adjusting the quantum gate parameters in heart disease prediction. The advantages include the use of quantum gates to explore high-dimensional space and their ability to reliably represent and predict features compared with traditional models.

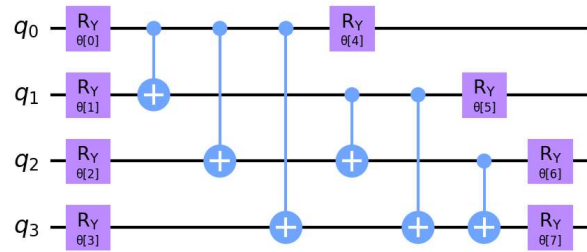


Figure-2: Structure of the VQC model

2.7.3 Measurement and Classifications

The measurement is executed in computational basis at the end of the quantum circuit.

$$M = \langle \psi_\theta(x) | Z_i | \psi_\theta(x) \rangle$$

Where Z_i acts on a qubit i . The Z_i is the Pauli operator which is used to measure the probability of specific outcomes.

$$\langle Z \rangle = \sum_i p_i z_i$$

The entropy loss function is used as a classical loss function:

$$L(0) = - \sum_i y_i \log(p_i) + (1 - y_i) \log(1 - p_i)$$

The probability of measuring a state $|1\rangle$ matches with the heart disease probability predicted (p_i). The patient's disease is classified as having heart disease (class 1) when the probability exceeds a threshold, rather than being healthy (class 0). The classical loss function and the quantum circuit parameters store measurement results to improve the accuracy of heart disease prediction. While applying gradient-based methods, the parameters θ are optimized. The VQC can learn complex medical patterns by integrating quantum circuits with classical optimization, offering advantages over existing ML models. However, quantum hardware is still in its early stages for heart disease prediction. Using VQC provides a reliable direction for QML in healthcare applications.

2.7.4 Training

During training, our primary goal is to find optimal parameter values that minimize the loss function. The optimization process in the quantum model and the classical neural network follows a similar approach. It involves three steps: first, performing a forward pass to make predictions; second, computing the loss; and third, updating the parameters based on the gradient. Mean Squared Error (MSE) is used as the loss function in training,

measuring the squared difference between actual and predicted values. The optimizer used for training is ADAM.

$$L = \frac{1}{n} \sum_{i=1}^n (y_i^{truth} - f(w, b, x_i))^2$$

The Adaptive Moment Estimation Algorithm (ADAM) is a gradient-based optimization algorithm that combines the benefits of two other optimization algorithms, namely Momentum and RMSProp, for optimizing the loss function. Adam adjusts learning rates for each parameter using the first and second moments of the gradients, enabling adaptive learning and faster convergence.

3. Experimental Setup

Data on heart disease from repositories such as the UCI Heart Disease Dataset [16] is refined through feature scaling and encoding. Simulations are performed on IBM Quantum Experience (IBM Q) and local quantum simulators. In contrast, hardware testing is conducted on IBM’s QASM simulator and real quantum devices such as IBM’s 5-qubit superconducting processors. An 8-core high-performance workstation with an Intel Core i7 processor, 32GB RAM, and an NVIDIA RTX 3090 GPU handles classical computations to enhance training. To ensure convergence, a hybrid quantum-classical framework uses optimizers such as Adam to refine quantum variational parameters.

3.1 Result and Discussion

This section presents simulation results for the proposed VQC model for predicting and classifying heart disease. The study collects patient data from the UCI Heart Disease Dataset, which is publicly available on Kaggle. The input data is split into two phases: training and testing, in an 80:20 ratio.

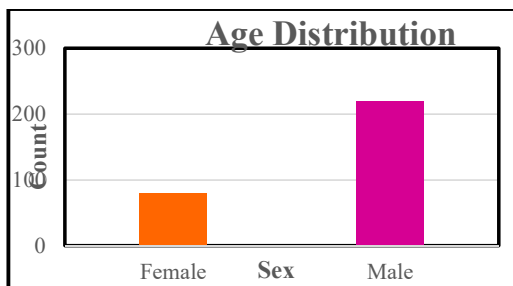


Figure-3 Gender-wise Distribution

Figure 3 shows a bar graph of age distribution by gender, with the x-axis showing male and female categories and the y-axis showing the counts of individuals. The orange represents the female category, with a count of around 80, and the pink color represents the male category, with a count of

around 220. This dataset shows that the number of male IDs is three times that of female IDs. The difference between the two gender populations is visualized effectively in this graph. Figure 4 shows the relationships between the features and their correlation coefficients, visualizing the strength and direction of each relationship. The highest positive correlations in Figure 4 include angina (exam), indicating that it strongly influences the target. Also, the highly positive correlation features are chest pain type (CP) and ST depression (old peak), with values around 0.5 to 0.6, indicating they are essential for impact. The medium positive correlation for the gender feature, around 0.25, refers to a weaker relationship with the target. The weaker correlations, such as resting blood pressure (trestbpps), cholesterol (chol), and fasting blood sugar (FBS), with correlation rates of around 0.1 to 0.2, indicate that they are limited but effective. The slight negative correlations for resting ECG (restecg) and maximum heart rate (thali), at -0.1 and -0.15, indicate a negligible impact on the target variables given their very low correlation. This bar graph shows that the strong predictor target models are cp, exang, and oldpeak, while the contributions of the models’ thali and respect in predicting the target are minimal. This analysis is essential for a clear understanding of the features and for optimizing model performance.

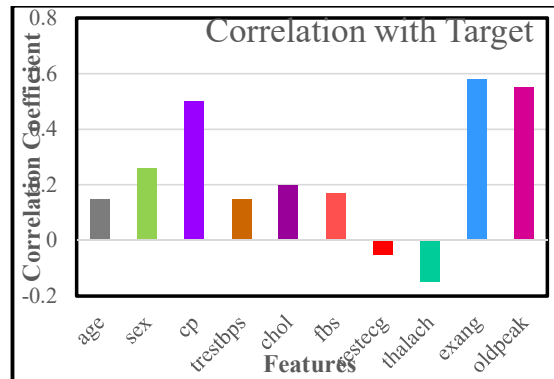


Figure-4: Multiple Features Of Input Samples

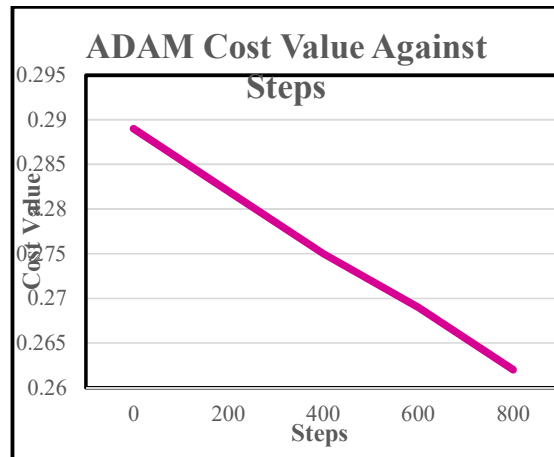


Figure-5: ADAM Cost Value Result

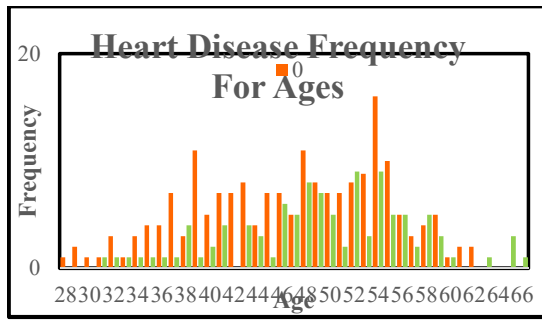


Figure-6: Patients' Age-Wise Distribution: With And Without Heart Diseases

This graph shows the relationship between cost and the number of steps using the ADAM algorithm. The x-axis represents the steps, and the y-axis represents the cost value. The cost value is around 0.29 at the initial step and around 0.26 at step 800. The cost value declines continuously from around 0.29 to 0.26, indicating effective minimization. A smooth decline indicates stable convergence and efficient optimization, thereby enhancing model performance. Figure-6 shows the frequency of heart disease cases across age groups. The x-axis represents patients' ages, and the y-axis represents the frequency of heart disease. There are two categories of heart disease. According to this graph, 0 (orange) indicates that patients are unhealthy without a heart disease diagnosis, and 1 (green) suggests that patients are healthy but have been diagnosed with heart disease. By observing this graph, heart disease is more common in patients aged between 40 and 60; both healthy (0) and diseased (1) patients exhibit a higher frequency. The number of cases among patients aged 52 to 55 is at its peak, but patients aged 54 are healthier than those aged 52. The green bar indicates that heart disease cases are spread more frequently than non-diseased cases. This trend, which represents high-risk patients aged 40 to 60, underscores the need for targeted health interventions in this group.

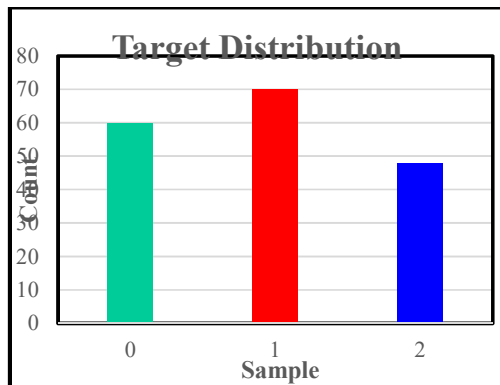


Figure-7. Target Distribution

Figure-7 shows the distribution of target variables across three categories: 0 (No heart diseases), 1 (With Heart Diseases), and 2 (Other Health Issues). The x-axis shows the categories, and the y-axis shows the count. Category 1 (red) has the highest count, around 70, indicating it is the most frequent in the dataset. Category 0 (green) follows with around 60, while Category 2 (blue) has the lowest count at approximately 45. This target distribution indicates that the dataset is balanced, except for Category 1, which is slightly higher, potentially impacting model training and classification. Proper handling, such as class weighting or resampling, is required to ensure fair model performance for all target classes.

4. Conclusion

The VQC application for heart disease diagnosis has significant potential due to its ability to process high-dimensional data, optimize feature extraction, and manage dataset noise. Quantum computing robustness, including superposition and entanglement, is uniquely leveraged in combination with classical optimization approaches, enabling the VQC to improve accuracy and effectiveness in heart disease classification. As a result, it provides early intervention in clinical diagnostics and reliability, equipping medical practitioners with tools for early diagnosis and treatment. Apart from the benefits, there are issues concerning the VQC model's functional application. The challenges are quantum hardware noise, limited qubit access, and the high complexity of hybrid quantum-classical optimization, which pose significant constraints on the VQC-based system's extensibility and performance. Quantum circuit optimization and integration with classical segments in a continuous, efficient manner are computationally intensive. The ongoing evolution of quantum hardware and the advancement of hybrid algorithms suggest that the VQC model for real-time, functional use in heart disease diagnosis will become a reality. After the challenges are addressed, VQC efficiency in the evolution of clinical diagnosis is likely to increase, providing quicker, more efficient, more accurate, and more economical solutions for heart disease diagnosis.

In the future, focus will be on enhancing the performance of the proposed VQC model by integrating it with explainable quantum error mitigation techniques. This will improve model performance in processing large-scale medical datasets and performing multi-class classification. A hybrid quantum deep learning model will be implemented to improve the model's reliability and scalability.

References

- 1.M. Schuld, A. Bocharov, K. Svore, and N. Wiebe, "Circuit-centric quantum classifiers," *Phys. Rev. A*, vol. 101, no. 3, pp. 032308, 2020.
- 2.A. Mari, T. R. Bromley, J. Izaac, M. Schuld, and N. Killoran, "Transfer learning in hybrid classical-quantum neural networks," *Quantum*, vol. 4, p. 340, 2020.
- 3.J. Chen, Y. Li, and X. Wang, "Quantum neural networks for medical data classification," *Journal of Biomedical Informatics*, vol. 116, p. 103752, 2021.
- 4.Y. Li, H. Liu, and J. Zhang, "Quantum support vector machine for cardiovascular disease prediction," *Computational and Structural Biotechnology Journal*, vol. 19, pp. 5800–5811, 2021.
- 5.J. Glick, M. Lin, and P. J. Coles, "Quantum perceptron for biomedical data," *npj Quantum Information*, vol. 7, no. 1, p. 106, 2021.
- 6.S. Rajora, A. Tripathi, and R. Arora, "A hybrid quantum-classical framework for cardiovascular disease diagnosis," *Applied Soft Computing*, vol. 114, p. 107749, 2022.
- 7.M. Cerezo et al., "Variational quantum algorithms," *Nature Reviews Physics*, vol. 3, pp. 625–644, 2021.
- 8.P. Zhao, C. Benedetti, and M. Fiorentini, "Quantum Boltzmann machine for probabilistic health prediction," *Quantum Machine Intelligence*, vol. 2, no. 1, pp. 5, 2020.
- 9.K. Yano, S. Yamamoto, and M. Kubo, "Quantum-enhanced diagnosis of infectious diseases with limited data," *IEEE Access*, vol. 9, pp. 158432–158440, 2021.
10. E. Farhi and H. Neven, "Classification with quantum neural networks on near term processors," *arXiv preprint arXiv:1802.06002*, 2018.
11. S. McArdle, S. Endo, A. Aspuru-Guzik, S. Benjamin, and X. Yuan, "Quantum computational chemistry," *Rev. Mod. Phys.*, vol. 92, no. 1, p. 015003, 2020.
12. M. Abdelsalam, A. Elsheikh, and D. Fan, "Quantum machine learning benchmark for healthcare datasets," *IEEE Transactions on Emerging Topics in Computing*, 2022 (Early Access).
13. A. Pérez-Salinas, A. Cervera-Lierta, E. Gil-Fuster, and J. I. Latorre, "Data re-uploading for a universal quantum classifier," *Quantum*, vol. 4, p. 226, 2021.
14. S. Manzeli, A. A. Hafiz, and M. Ahmed, "Quantum-enhanced feature selection and classification for biosignal data," *Frontiers in Artificial Intelligence*, vol. 6, p. 101234, 2023.
15. K. Bharti et al., "Noisy intermediate-scale quantum algorithms," *Rev. Mod. Phys.*, vol. 94, no. 1, p. 015004, 2022.
16. <https://www.kaggle.com/datasets/immikhilan/and/heart-attack-prediction>