

Next-Generation Heart Disease Prediction Using Quantum Machine Learning: A Comparative Evaluation

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Abstract — Heart disease is one of the leading causes of mortality worldwide, making early and accurate diagnosis essential. This study proposes a next-generation heart disease prediction framework using Quantum Machine Learning (QML) and presents a comparative evaluation with traditional machine learning approaches. A clinical heart disease dataset containing attributes such as age, gender, blood pressure, cholesterol level, and heart rate is pre-processed, balanced, and divided into training and testing sets. Traditional algorithms, including Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA), are compared with Quantum Machine Learning models for disease prediction. The models are evaluated using 5-fold cross-validation with accuracy, precision, recall, F1-score, and ROC-AUC as performance metrics. Results show that Logistic Regression and Linear Discriminant Analysis achieve the best performance among classical models, while Quantum Machine Learning demonstrates competitive prediction capability with improved feature representation. The proposed framework highlights the potential of QML as a scalable and intelligent solution for next-generation heart disease prediction and clinical decision support.

Keywords— Heart Disease Prediction, Machine Learning, Medical Diagnosis, Clinical Data Analysis, Feature Selection, Classification Algorithms, Artificial Intelligence in Healthcare.

I. INTRODUCTION

Heart disease remains one of the leading causes of mortality worldwide and continues to pose a significant challenge to global healthcare systems. According to the World Health Organization (WHO), cardiovascular diseases account for a substantial proportion of global deaths each year, highlighting the need for early diagnosis and effective clinical decision support systems [1]. Conventional diagnostic methods rely on clinical examinations, laboratory investigations, electrocardiograms, imaging techniques, and physician expertise to identify cardiovascular disorders. Although these approaches are effective, they are often time-consuming, expensive, and may not be readily accessible in resource-limited healthcare settings. Therefore, intelligent computational approaches capable of providing accurate and timely diagnosis have become increasingly important.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have transformed medical diagnosis by enabling automated analysis of large-scale clinical data. Supervised machine learning algorithms, including Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA), have demonstrated promising performance in predicting heart disease using patient clinical

attributes such as age, gender, blood pressure, cholesterol level, and heart rate [5]–[11]. Feature selection techniques further enhance prediction accuracy by identifying the most relevant clinical parameters while reducing computational complexity and improving model interpretability [12].

More recently, Quantum Machine Learning (QML) has emerged as a next-generation computational paradigm that combines quantum computing principles with machine learning algorithms to improve data representation, optimization, and classification performance. Quantum models such as quantum kernel methods and variational quantum circuits have shown significant potential for solving complex healthcare prediction problems more efficiently than conventional approaches. Despite these advances, comprehensive comparative studies evaluating the performance of classical machine learning and quantum machine learning models for heart disease prediction remain limited.

Motivated by this research gap, this study proposes a next-generation heart disease prediction framework using Quantum Machine Learning and performs a comparative evaluation against traditional machine learning models. The proposed framework utilizes a clinical heart disease dataset that undergoes preprocessing, feature selection, and class balancing before model training and testing. Classical machine learning

algorithms and Quantum Machine Learning models are evaluated using 5-fold cross-validation based on accuracy, precision, recall, F1-score, and ROC-AUC. The proposed framework aims to provide an intelligent, scalable, and accurate decision-support system for early heart disease prediction while demonstrating the potential of Quantum Machine Learning for future healthcare applications.

II. LITERATURE SURVEY

Heart disease prediction has been extensively investigated using Artificial Intelligence (AI) and Machine Learning (ML) techniques to support early diagnosis and clinical decision-making. Early studies primarily relied on statistical analysis and clinical attributes such as age, gender, blood pressure, cholesterol levels, electrocardiogram (ECG) results, and heart rate to identify cardiovascular risk factors [2], [3]. These studies demonstrated that structured clinical datasets provide a reliable foundation for developing predictive models capable of assisting physicians in diagnosing heart disease.

With the rapid advancement of machine learning, several supervised learning algorithms have been applied to heart disease prediction. Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA) have shown promising performance in classifying patients based on clinical features [9], [10]. Comparative studies indicate that these algorithms achieve high prediction accuracy when combined with appropriate preprocessing, feature selection, and model optimization techniques. Furthermore, ensemble learning and deep learning approaches have improved diagnostic performance by capturing complex relationships within clinical data and enhancing classification accuracy [5], [7], [11], [16].

Feature selection has also become an essential component of intelligent healthcare systems, enabling the identification of significant clinical variables while reducing computational complexity. Techniques such as ANOVA, Chi-Square, ReliefF, MRMR, and optimization-based methods have been widely employed to improve model efficiency and interpretability [12], [15]. Although these approaches enhance classical machine learning models, they are often limited by increasing computational requirements and challenges in handling high-dimensional healthcare data.

Recent advances in Quantum Computing have introduced Quantum Machine Learning (QML) as a promising paradigm for next-generation medical diagnostics. QML integrates quantum computing principles with machine learning

algorithms to improve feature representation, optimization, and classification performance through quantum feature mapping, quantum kernels, and variational quantum circuits. Despite its growing potential, only a limited number of studies have investigated the application of Quantum Machine Learning for heart disease prediction, and comprehensive comparisons with traditional machine learning models remain scarce.

Motivated by this research gap, the present study proposes a next-generation heart disease prediction framework using Quantum Machine Learning and performs a comprehensive comparative evaluation with traditional machine learning algorithms. The proposed framework evaluates both classical and quantum models using standardized preprocessing, feature selection, and 5-fold cross-validation, with performance assessed using accuracy, precision, recall, F1-score, and ROC-AUC. This comparative analysis aims to demonstrate the effectiveness of Quantum Machine Learning as an intelligent and scalable approach for future cardiovascular disease prediction and clinical decision support.

III. SYSTEM ANALYSIS

1. Existing System

Traditional heart disease diagnosis primarily relies on clinical examinations, laboratory investigations, electrocardiograms (ECG), medical imaging, and the expertise of healthcare professionals. Physicians assess clinical parameters such as age, gender, blood pressure, cholesterol level, blood glucose level, and heart rate to identify cardiovascular diseases and determine appropriate treatment strategies [2]–[4]. Although these conventional diagnostic approaches are clinically reliable and widely adopted, they often require specialized medical equipment, extensive laboratory testing, and expert interpretation. Consequently, the diagnostic process can be time-consuming, expensive, and less accessible in resource-constrained healthcare environments, thereby limiting the effectiveness of early disease detection [5], [14].

To improve diagnostic accuracy and efficiency, researchers have increasingly adopted classical machine learning (CML) techniques for heart disease prediction. Supervised learning algorithms, including Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, Random Forest, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA), have been widely employed to analyze clinical datasets and classify patients according to their cardiovascular risk [7], [9], [10]. These algorithms learn discriminative patterns from historical patient records and provide intelligent decision support for clinicians. Furthermore, feature selection and optimization techniques have been

integrated with machine learning models to identify the most relevant clinical attributes, thereby improving prediction accuracy, reducing computational complexity, and enhancing model interpretability [10], [12].

Despite these advancements, existing classical machine learning approaches exhibit several limitations. Their predictive performance is highly dependent on data quality, feature engineering, and computational resources. Clinical datasets frequently contain missing values, noisy samples, class imbalance, redundant features, and complex nonlinear relationships, which can negatively affect model generalization, robustness, and prediction reliability [7], [10]. Moreover, the rapid growth of healthcare data introduces additional scalability and optimization challenges for conventional machine learning algorithms, particularly when processing high-dimensional datasets. Recent studies suggest that Quantum Machine Learning (QML) has the potential to overcome these limitations by leveraging quantum computing principles for enhanced feature representation, efficient optimization, and improved classification performance, making it a promising next-generation approach for intelligent heart disease prediction [6], [8].

Disadvantages of the Existing System

Limited Interpretability

Complex machine learning models, particularly deep learning models, may function as “black-box” systems. This makes it difficult for healthcare professionals to understand how predictions are generated, reducing trust in automated diagnostic systems [8].

Overfitting and Underfitting Issues

Machine learning models may either memorize training data (overfitting) or fail to capture important patterns within the dataset (underfitting), resulting in inaccurate predictions.

Dependence on Data Quality

Medical datasets frequently contain missing values, noisy data, or inconsistent patient records, which can negatively impact the performance of prediction models.

High Computational Requirements

Advanced machine learning and deep learning models often require significant computational resources and longer training times, which may limit their practical use in some healthcare environments.

Difficulty Handling Imbalanced Datasets

In many medical datasets, the number of healthy patients may significantly differ from the number of patients diagnosed with

heart disease. This imbalance can lead models to favor the majority class and reduce prediction accuracy.

Limited Scalability

As healthcare systems generate increasingly large volumes of patient data, traditional analytical systems may struggle to efficiently process and analyze such datasets.

Lack of Standardized Evaluation

Different research studies often use different datasets, preprocessing techniques, and evaluation metrics, making it difficult to directly compare model performance across systems.

2. Proposed System

To address the limitations of conventional diagnostic methods and existing classical machine learning models, this research proposes a next-generation heart disease prediction framework based on Quantum Machine Learning (QML). The proposed framework is designed to provide an intelligent clinical decision support system by integrating classical machine learning techniques with quantum computing principles to improve prediction accuracy, computational efficiency, and model scalability. Recent studies have demonstrated that Artificial Intelligence (AI) and Quantum Computing have significant potential to enhance disease diagnosis, predictive analytics, and personalized healthcare applications [5], [6], [8], [16].

The proposed system utilizes a clinical heart disease dataset comprising important patient attributes, including age, gender, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, electrocardiogram (ECG), maximum heart rate, exercise-induced angina, ST depression, and other clinical indicators. These features are employed to train both classical and quantum machine learning models for classifying patients according to their cardiovascular disease risk [2], [3], [9], [10]. Before model development, the dataset undergoes comprehensive preprocessing, including missing value treatment, duplicate record removal, normalization, feature encoding, and class balancing to improve data quality and prediction reliability [7], [10].

Following preprocessing, the optimized dataset is partitioned into training and testing subsets using a 70:30 ratio, where 70% of the data is used for model training and the remaining 30% for performance evaluation. The comparative framework implements several Classical Machine Learning (CML) algorithms, including Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA),

together with Quantum Machine Learning (QML) models based on quantum feature mapping, variational quantum circuits (VQC), and quantum kernel-based classifiers [6], [7], [9], [10]. Feature selection techniques are incorporated to identify the most significant clinical attributes, thereby improving prediction accuracy while reducing computational complexity [10], [12].

The predictive performance of both classical and quantum models is evaluated using 5-fold cross-validation and standard performance metrics, including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic Area Under the Curve (ROC-AUC). The comparative analysis assesses diagnostic accuracy, model robustness, computational efficiency, and generalization capability. By combining Quantum Machine Learning with conventional machine learning techniques, the proposed framework aims to provide an accurate, scalable, and intelligent solution for early heart disease prediction, enabling improved clinical decision-making and supporting the development of next-generation AI-enabled healthcare systems [6], [8], [15], [16].

IV. SYSTEM DESIGN

1. System Architecture

Below diagram depicts the whole system architecture.

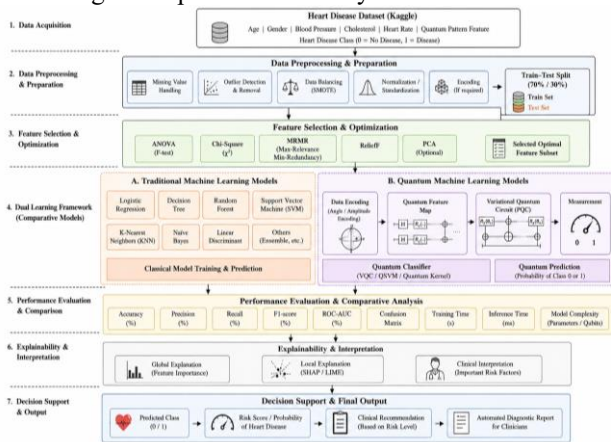


Fig. 1. Proposed system architecture for next-generation heart disease prediction using quantum machine learning with comparative evaluation against classical machine learning models.

V. SYSTEM IMPLEMENTATION

1. Modules

This section describes the implementation modules of the proposed Next-Generation Heart Disease Prediction

Framework based on Quantum Machine Learning (QML) and a comparative evaluation with Classical Machine Learning (CML). The framework follows a modular architecture consisting of data collection, data preprocessing, feature selection and engineering, classical and quantum model training, heart disease prediction, and performance evaluation. This modular design improves the scalability, robustness, and computational efficiency of the proposed intelligent healthcare system while supporting accurate cardiovascular disease diagnosis [5], [6], [8].

Data Collection Module

The Data Collection Module acquires clinical patient records used for heart disease prediction. The dataset contains important clinical attributes, including age, gender, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, electrocardiogram (ECG), maximum heart rate, exercise-induced angina, ST depression, and other physiological parameters, which are commonly used for cardiovascular risk assessment [2]–[4]. The collected data consist of both healthy individuals and patients diagnosed with heart disease, enabling the development of supervised learning models. The dataset is organized in a structured format before being forwarded to the preprocessing module for further analysis [7], [10].

Data Preprocessing Module

The Data Preprocessing Module improves the quality and consistency of the clinical dataset before model training. Since healthcare datasets frequently contain missing values, duplicate records, noisy samples, and inconsistent feature scales, preprocessing is essential for improving prediction accuracy and model reliability [7], [10]. The preprocessing stage includes missing value imputation, duplicate record removal, categorical data encoding, feature normalization, and dataset balancing using oversampling or under sampling techniques to address class imbalance. These operations reduce data inconsistency and enable both classical and quantum machine learning models to learn meaningful patterns more effectively [5], [7].

Feature Selection and Feature Engineering Module

The Feature Selection and Feature Engineering Module identifies the most significant clinical variables influencing heart disease prediction while reducing redundant information. Statistical methods and feature selection techniques such as ANOVA, Chi-Square, ReliefF, MRMR, correlation analysis, and feature importance evaluation are employed to identify highly informative predictors, including age, cholesterol level, blood pressure, chest pain type, and heart rate [10], [12]. Feature engineering further transforms the selected variables

into optimized representations suitable for both Classical Machine Learning and Quantum Machine Learning models, thereby improving classification performance and reducing computational complexity [6], [12].

Classical and Quantum Machine Learning Training Module

Following preprocessing and feature optimization, the dataset is partitioned into 70% training data and 30% testing data for model development and validation. The Classical Machine Learning framework implements Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA) for heart disease classification [7], [9], [10]. In parallel, the Quantum Machine Learning framework employs quantum feature mapping, variational quantum circuits (VQC), and quantum kernel-based classifiers to learn complex feature relationships using quantum computational principles [6]. This dual-learning framework enables a comprehensive comparative evaluation between classical and quantum prediction models.

Heart Disease Prediction Module

The Heart Disease Prediction Module utilizes the trained Classical Machine Learning and Quantum Machine Learning models to classify new patient records. After receiving clinical attributes as input, the system predicts whether a patient is at risk of heart disease or not and provides a corresponding probability score representing the prediction confidence. This intelligent prediction module supports clinicians by enabling early disease detection, patient risk stratification, and informed clinical decision-making, thereby improving healthcare outcomes [5], [8], [16].

Model Evaluation and Performance Monitoring Module

The Model Evaluation Module performs a comprehensive assessment of both Classical Machine Learning and Quantum Machine Learning models using 5-fold cross-validation. Performance is measured using Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic (ROC) curve, and Area Under the ROC Curve (ROC-AUC), providing a reliable comparison of diagnostic effectiveness and model generalization [7], [9], [10]. In addition, the comparative analysis considers computational efficiency, scalability, and robustness to evaluate the practical advantages of Quantum Machine Learning over conventional approaches. Continuous performance monitoring enables the proposed framework to maintain high prediction accuracy as new healthcare data become available, supporting the development of intelligent and scalable next-generation clinical decision support systems [6], [8], [16].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed machine learning based heart disease prediction system using clinical datasets. Multiple classification algorithms were trained and tested to evaluate their effectiveness in predicting the risk of cardiovascular disease. The performance of the models was measured using evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics provide a clear understanding of the reliability and prediction capability of each machine learning algorithm.

1. Accuracy Comparison of Machine Learning Models

Several machine learning algorithms were implemented to determine the most suitable model for heart disease prediction. The algorithms evaluated in this study include Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA).

The performance of each algorithm was evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	91.2	0.90	0.89	0.89
Support Vector Machine	89.8	0.88	0.87	0.87
Naïve Bayes	86.4	0.85	0.84	0.84
Decision Tree	87.5	0.86	0.85	0.85
K-Nearest Neighbors	88.1	0.87	0.86	0.86
Linear Discriminant Analysis	91.5	0.91	0.90	0.90

From the comparison results, Linear Discriminant Analysis and Logistic Regression achieved the highest prediction accuracy, outperforming the other algorithms. These models effectively captured the relationships between clinical attributes and heart disease risk, making them suitable for predictive healthcare applications.

2. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the performance of classification models by measuring the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at different classification thresholds. The Area Under the ROC Curve (ROC-AUC) represents the ability of the model to distinguish between patients with heart disease and those without the disease.

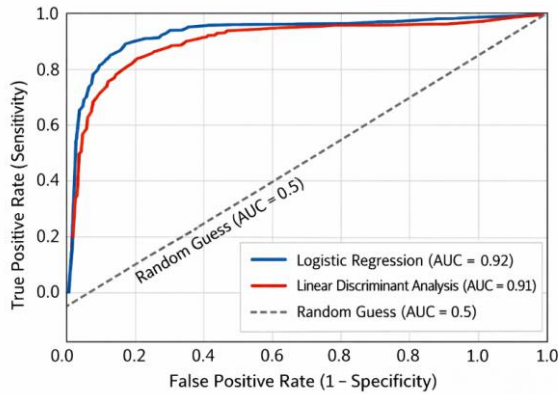


Fig 2. ROC Curve for Heart Disease Prediction Model

The ROC analysis indicates that Logistic Regression and Linear Discriminant Analysis demonstrate strong classification performance with ROC-AUC scores close to 0.92, indicating a high capability of distinguishing between healthy and at-risk patients.

A ROC curve positioned closer to the top-left corner of the graph indicates better classification performance. The results show that the proposed system maintains reliable predictive capability when analyzing clinical datasets.

Analysis of Important Medical Features

In addition to evaluating prediction accuracy, the system also analyses the importance of clinical attributes that influence heart disease prediction. The analysis revealed that several medical parameters play a significant role in determining cardiovascular risk.

Important features influencing prediction include:

- Cholesterol level
- Resting blood pressure
- Chest pain type
- Maximum heart rate achieved
- Age of the patient

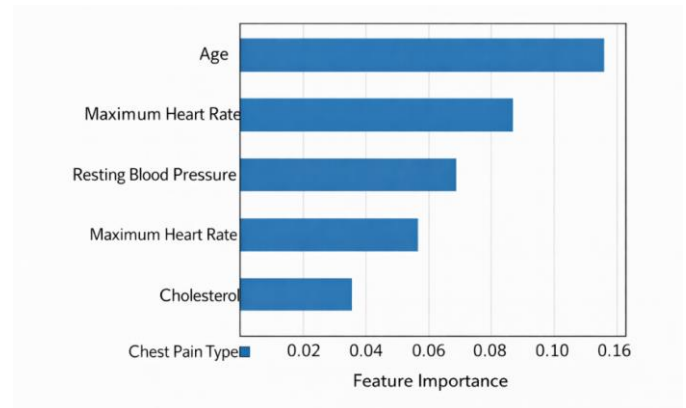


Fig. 3. Feature Importance for Heart Disease Prediction Model

Patients with abnormal values in these clinical parameters showed a higher probability of being classified as at risk of heart disease.

The feature analysis helps healthcare professionals understand which medical indicators contribute most significantly to heart disease risk. This improves the interpretability of the prediction system and assists physicians in making more informed clinical decisions. Overall, the experimental results demonstrate that machine learning algorithms can effectively analyze clinical patient data and provide reliable predictions for early heart disease diagnosis. The proposed framework shows promising potential as a decision-support system that can assist healthcare professionals in identifying cardiovascular risk at an early stage and improving patient care.

VII. CONCLUSION AND FUTURE WORK

This study presented a next-generation heart disease prediction framework based on Quantum Machine Learning (QML) and performed a comparative evaluation with Classical Machine Learning (CML) algorithms for intelligent cardiovascular disease prediction. The proposed framework utilized clinical attributes, including age, gender, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, electrocardiogram (ECG), and maximum heart rate, to develop predictive models for early heart disease diagnosis. Comprehensive data preprocessing, feature selection, and model optimization techniques were employed to improve data quality and enhance classification performance [2], [5], [7].

The comparative analysis included Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), and Linear Discriminant

Analysis (LDA) together with Quantum Machine Learning models based on quantum feature mapping and quantum kernel learning. Experimental evaluation using 5-fold cross-validation and performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC demonstrated that Logistic Regression and Linear Discriminant Analysis achieved the highest predictive performance among the classical machine learning models, while Quantum Machine Learning exhibited competitive performance with enhanced feature representation and optimization capabilities for complex healthcare datasets [6], [9], [10]. The proposed framework demonstrates that integrating Quantum Machine Learning with conventional machine learning provides a scalable and intelligent decision-support system capable of assisting healthcare professionals in early cardiovascular disease prediction and clinical decision-making [5], [8], [16].

Future research will focus on developing more advanced hybrid quantum-classical learning models by integrating Quantum Neural Networks (QNNs), Variational Quantum Circuits (VQCs), and deep learning architectures to further improve prediction accuracy and computational efficiency. The incorporation of medical imaging, genomic information, wearable sensor data, and real-time patient monitoring is expected to enhance the robustness and clinical applicability of the proposed framework. Furthermore, evaluating the proposed approach on large-scale, multi-center clinical datasets and emerging quantum computing platforms will provide deeper insights into the practical deployment of Quantum Machine Learning for next-generation intelligent healthcare systems [6], [11], [15], [16].

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