

RESEARCH ARTICLE

Quantum Machine Learning for Early Detection of Heart Disease: Implementing HQNN and QCVNET Frameworks for Clinical Decision Support

Md Anjar Ahsan^{1,*}, Akif Jawaid²

ABSTRACT: Cardiovascular diseases (CVDs) continue to be the leading global cause of death, requiring innovative approaches for early detection and accurate prediction. This study explores the transformative potential of quantum-enhanced machine learning (quqml) models in cardiovascular disease prediction, addressing the limitations of conventional diagnostic approaches. Using extensive datasets including the Kaggle Heart Disease Dataset of 1,190 patient records and the Cleveland/State Registry datasets, the quantum-enhanced models show superior performance over traditional machine learning approaches, with QCVNET achieving 91.73% accuracy and quqml showing a 0.6% improvement in accuracy, while reducing training time from 862.5 μ s to 670 μ s per cycle. Key physiological parameters including diabetes indicators, LDL cholesterol, HDL cholesterol, and triglycerides were incorporated as predictive features. The IQCNN framework achieved 91% classification accuracy at a learning rate of 70%, significantly outperforming the Bi-LSTM and CNN approaches. Comparative analysis revealed exceptional AUC scores of 96.43% and 97.78% for the hybrid models, establishing quantum-enhanced machine learning as a highly effective solution for cardiovascular risk assessment and early detection systems.

Keywords: Quantum Machine Learning (QuEML), Cardiovascular Disease Prediction, Quantum Convolutional Neural Network (QCVNET), Hybrid Quantum Neural Network (HQNN), Deep Learning

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1. INTRODUCTION

Cardiovascular diseases (CVDs) pose a global health burden, necessitating accurate and timely prediction models. To improve the accuracy of heart disease prediction, scientists have combined quantum computing with deep learning methods [1]. One innovative solution is the Quantum Convolutional Neural Network (QCVNET), which integrates quantum computing layers into a traditional Convolutional Neural Network (CNN) architecture. The QCVNET model

uses a large dataset that includes medical and demographic records and incorporates principal component analysis (PCA) to maintain feature consistency with the number of quantum bits (qubits) [2-4]. Demonstrating exceptional performance, QCVNET achieved 91.73% accuracy in early cardiovascular disease (CVD) prediction. This result outperformed not only other quantum-based models, including quantum LSTM, quantum DNN, quantum GRU, and quantum RNN, but also classical machine learning approaches such as SVM, RF, RNN, and DNN. QCVNET's success underscores the transformative potential of quantum-enhanced deep learning in enabling early detection and tailored treatment plans, ultimately helping to reduce the global impact of cardiovascular diseases [5-9]. Recent advances in quantum computing open up novel avenues for machine learning applications, particularly in improving clinical diagnostics for complex conditions such as cardiovascular diseases. This

¹ Department of Computer Science, Lords Institute of Engineering and Technology, Hyderabad, India

² Department of Computer Science, Maulana Azad National Urdu University, Hyderabad, India

* Author to whom correspondence should be addressed:
anjarahsan@gmail.com (M. A. Ahsan)

research systematically evaluates the performance of quantum-enhanced machine learning (QuEML) models in predicting heart disease. For comparative analysis, this study uses the Kaggle heart disease dataset of 1,190 patient records (53% diagnosed cases vs. 47% healthy controls) to benchmark QuEML against conventional machine learning approaches [2].

The performance evaluation included key metrics including precision, accuracy, recall, specificity, F1-score, and computational efficiency. The comparative analysis revealed QuEML's superior performance over conventional methods, achieving a 0.6% improvement in accuracy, while demonstrating significantly faster processing speed (an average reduction of 192.5 μ s per training cycle). Notably, QuEML correctly identified 50.03% of positive events and 44.65% of negative events, outperforming traditional approaches that achieved 49.78% and 44.31%, respectively. The computational advantage was particularly evident in training times, with QuEML requiring only 670 μ s compared to 862.5 μ s for classical algorithms. These findings position QuEML as a highly effective solution for cardiovascular disease prediction [3-5]. Cardiovascular diseases maintain their position as the leading global cause of death, with accurate prediction proving difficult due to the required clinical knowledge and diversity of diagnostic parameters.

Modern healthcare infrastructure has gradually adopted Internet of Things (IoT) platforms to collect physiological sensor data for cardiac condition monitoring and early detection. Although considerable research has been conducted on cardiac diagnostic systems, the consistency and reliability of the results continue to show considerable variation. In response to these challenges, we present a novel automated cardiovascular risk assessment framework that uses a three-phase architecture: data pre-processing, feature selection, and predictive analysis [4-7]. The pre-processing stage uses an improved Z-score normalization technique to standardize the input data. Following this, the feature extraction stage identifies discriminatory biomarkers, including refined entropy metrics, statistical parameters, and information gain attributes, from the normalized dataset to train an initial model. The system culminates in predictive analysis using an advanced quantum convolutional neural network (IQCNN).

Experimental results demonstrate the superior capability of IQCNN, achieving 91% classification accuracy at a 70% learning rate, significantly outperforming traditional approaches including Bi-LSTM, CNN, and other neural network types [6-9]. Cardiovascular diseases pose a global health burden, as evidenced by the increasing prevalence and mortality rates that have significant economic impacts worldwide. Consequently, developing accurate early prediction systems for cardiac disorders has become increasingly important to mitigate these multifaceted consequences. This study proposes two novel quantum machine learning frameworks for early detection: (1) a hybrid quantum neural network (HQNN) and (2) a hybrid random forest quantum neural network (HRFQNN) [7-12]. The proposed methods were rigorously evaluated using two key

datasets: the Cleveland and Stat log heart disease datasets. Experimental results demonstrate distinct advantages for each approach, such as the Hybrid Quantum Neural Network (HQNN) excels in handling high-dimensional data, while the Hybrid Random Forest Quantum Neural Network (HRFQNN) shows superior performance in low-dimensional situations [12-18]. In particular, HRFQNN shows greater robustness to outliers compared to HQNN, which is more sensitive to data variations. Comparative analysis with conventional machine learning techniques reveals the exceptional predictive ability of the quantum-enhanced models, as evidenced by excellent AUC scores of 96.43% (Cleveland dataset) and 97.78% (Stat log dataset), establishing their effectiveness for early cardiac risk assessment [19-23]. As the primary cause of death worldwide, heart disease is a serious health issue. The World Health Organization states that cardiovascular diseases (CVDs) claim more lives each year than any other health condition. The main objective is to create a smart quantum neural network-based heart disease prediction system that uses heart disease datasets to enable sophisticated clinical decision making beyond the capabilities of conventional decision support systems [24-27].

Heart disease (HD) presents a serious risk to public health worldwide because its high prevalence and increasing mortality rates, which put human well-being at risk. Early identification through measurable physical indicators is crucial to prevent disease progression and reduce long-term impacts. As a result, prevention strategies for HD have long been a major area of research. By analysing risk factors and their patterns in young adults, even before clinical symptoms appear, it is possible to predict the likelihood of future heart disease. By the time heart disease is identified, atherosclerosis, the underlying cause, has often been significantly advanced for many years [10, 28-31]. Cardiovascular diseases, including heart attacks, claim more than 17 million lives annually. Artificial intelligence holds the promise of transforming cardiology by supporting earlier and more accurate diagnoses, which are essential for effective treatment and management. AI-powered methods can analyse enormous volumes of data, identify trends, and forecast outcomes, offering useful assistance in diagnosing heart disease. Recent research and developments highlight the growing role of AI in this field.

2. DETAILS OF THE STUDY

2.1. Definitions of the parameters

Diabetes: The hallmark of diabetes is high blood glucose, or blood sugar, levels, which operate as the body's primary energy source. The body gets glucose from the food it eats, but it can also make it on its own. Insulin, A pancreatic hormone facilitates glucose's entry into cells, where it is converted to energy. Diabetes patients either create insufficient amounts of insulin or their bodies are unable to use it effectively, causing glucose to remain in the bloodstream instead of reaching the cells. This can lead to

problems affecting the heart, kidneys, nerves, and eyes, and may potentially raise the chance of developing some types of cancer. Managing or preventing diabetes is key to reducing the likelihood of these health problems.

LDL: LDL cholesterol, also called "bad" cholesterol, can accumulate on the walls of blood vessels and raise the risk of heart disease attack and stroke. However, cholesterol is not entirely harmless – it plays an important role in protecting nerves and producing healthy cells and hormones. Some cholesterol is obtained from food, while the liver also produces it. Because cholesterol does not dissolve in the blood, it is transported by proteins called lipoproteins. LDL, or low-density lipoprotein, is one such transporter.

LDL.1 (HDL): HDL stands for high-density lipoprotein. Each HDL particle has a protein outer layer surrounding a fatty core, making it denser than other types of cholesterol, hence the name "high density." Often referred to as "good" cholesterol, HDL helps protect your heart by circulating in your bloodstream and removing excess harmful cholesterol from areas where it can cause damage. A lower risk of heart disease is linked to high HDL levels, whereas low amounts can increase that risk.

Triglycerides: The majority of the dietary fats in butter are triglycerides, a type of fat that we obtain from our diet. Triglycerides are created by excess calories, sugar, and alcohol and are then deposited in fat cells throughout the body, similar to the shelves in a food pantry, to be used for energy when needed. High triglyceride levels, known as hypertriglyceridemia, significantly increase the danger of blood vessel and cardiac disorders, such as heart attacks and strokes. In the United States, about 25% of people have high triglyceride levels.

2.2. Instructions for machine learning

Ada Boost Regression: There are several solutions available in the realm of machine learning models, and Ada Boost is among them. It belongs to the family of advanced ensemble learning techniques and follows the boosted learning approach covered in our writings. The Ada Boost algorithm's basic concept involves using various subsets of the training data to train a number of weak classifiers. Every time the algorithm is used, increases the weight of previously misclassified samples, focusing on the most difficult cases. This iterative process helps subsequent weak classifiers better address challenging samples, thereby improving overall performance. In essence, adaptive boosting aims to lower any machine learning algorithm's error rate by integrating several weak samples into a single, more accurate strong model.

The data in [Table 1](#), titled Quantum Neural Network-Based Heart Disease Prediction, presents key biomedical parameters of diabetes, LDL, LDL.1 (HDL), and triglycerides collected for multiple subjects to run within the Quantum Neural Network (QNN) framework. These values, such as LDL from 70 to 160 and triglycerides from 149 to 499, represent a variety of health profiles that are essential for accurate prediction. By integrating and implementing these variables, the QNN model can learn complex patterns and relationships between lipid levels, glucose, and heart disease risks. This interoperability improves prediction accuracy, making it a valuable tool for early diagnosis and targeted health interventions.

Table 1. Quantum Neural Network-Based Heart Disease Prediction.

Diabetes	LDL	LDL.1(HDL)	Triglycerides
151.25	135.63	52.5	255.25
121.25	111.25	72.5	183.38
188.75	154.38	27.5	442.75
95	85	90	161.5
80	70	100	149
201	160	20	499
117.5	107.5	75	180.25
143.75	131.88	57.5	217.75
113.75	103.75	77.5	177.13
91.25	81.25	92.5	158.38
196.25	158.13	22.5	480.25
139	130	60	199
162.5	141.25	45	311.5
83.75	73.75	97.5	152.13
192.5	156.25	25	461.5
106.25	96.25	82.5	170.88
128.75	118.75	67.5	189.63
166.25	143.13	42.5	330.25
181.25	150.63	32.5	405.25
87.5	77.5	95	155.25
185	152.5	30	424
155	137.5	50	274
132.5	122.5	65	192.75
125	115	70	186.5
177.5	148.75	35	386.5
170	145	40	349
98.75	88.75	87.5	164.63
136.25	126.25	62.5	195.88
110	100	80	174
158.75	139.38	47.5	292.75
173.75	146.88	37.5	367.75
102.5	92.5	85	167.75
147.5	133.75	55	236.5

3. RESULTS AND DISCUSSIONS

[Table 2](#) presents summary measures for four key health

indicators: diabetes, LDL, LDL.1 (HDL), and triglycerides, which are operationalized within predictive health models. By standardizing these values (mean, standard deviation, quartiles, etc.), the dataset becomes operable in a variety of analytical frameworks, including quantum neural networks [11]. For example, the mean diabetes level is 140, with a standard deviation of 36.31, while triglycerides range from 149 to 499. Such statistical insights support data normalization and model calibration, which ensures consistent integration across different settings. This interoperability improves accuracy in disease prediction and

facilitates effective cross-platform clinical data analysis.

3.1. Effect of Process Parameters

Figure 1 presents a scatterplot matrix illustrating the relationships between health indicators such as diabetes, LDL, LDL_1, and triglycerides used in quantum neural network-based heart disease prediction. Each subplot highlights correlation patterns, where points exhibit linear or nonlinear correlations, and histograms on the diagonal reflect individual variable distributions.

Table 2. Descriptive Statistics.

	Diabetes	LDL	LDL.1(HDL)	Triglycerides
count	33.0000	33.0000	33.0000	33.0000
mean	140.0000	122.2739	60.0000	263.3952
std	36.3133	27.5728	24.1739	112.3197
min	80.0000	70.0000	20.0000	149.0000
25%	110.0000	100.0000	40.0000	174.0000
50%	139.0000	130.0000	60.0000	199.0000
75%	170.0000	145.0000	80.0000	349.0000
max	201.0000	160.0000	100.0000	499.0000

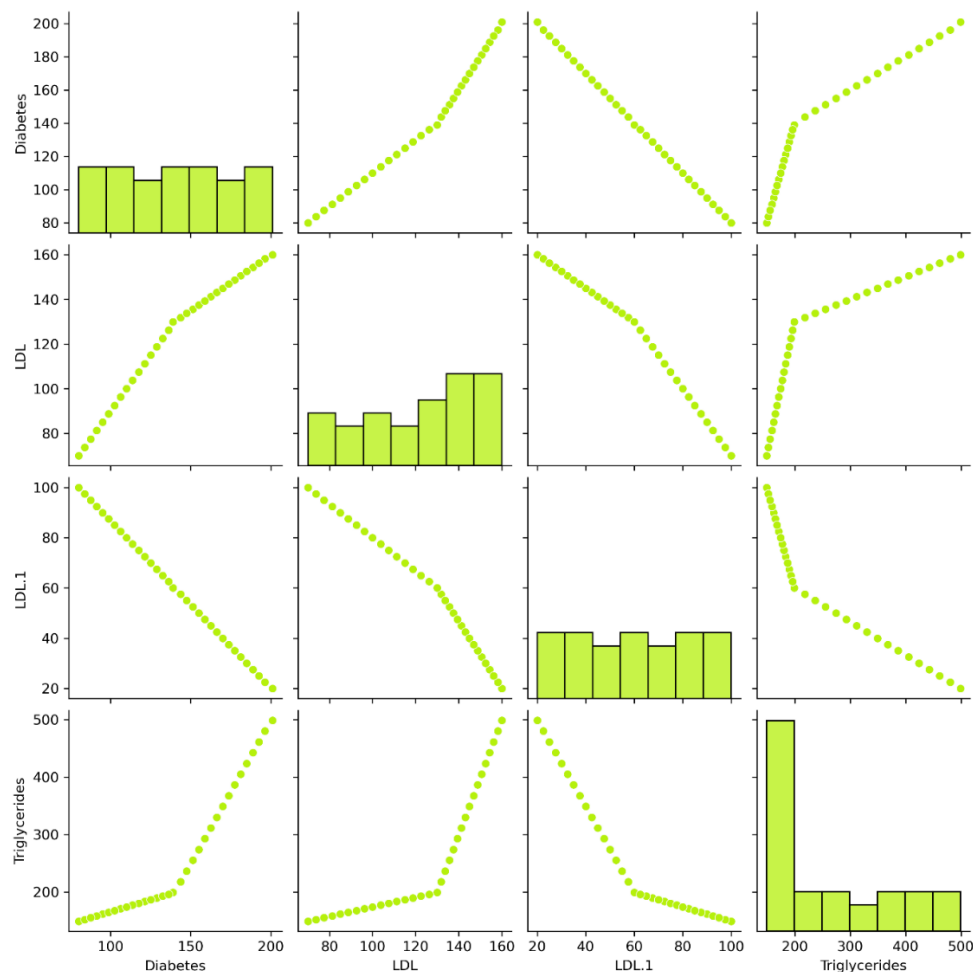


Fig. 1. Scatter plot depicting different Quantum Neural Network-Based Heart Disease Prediction.

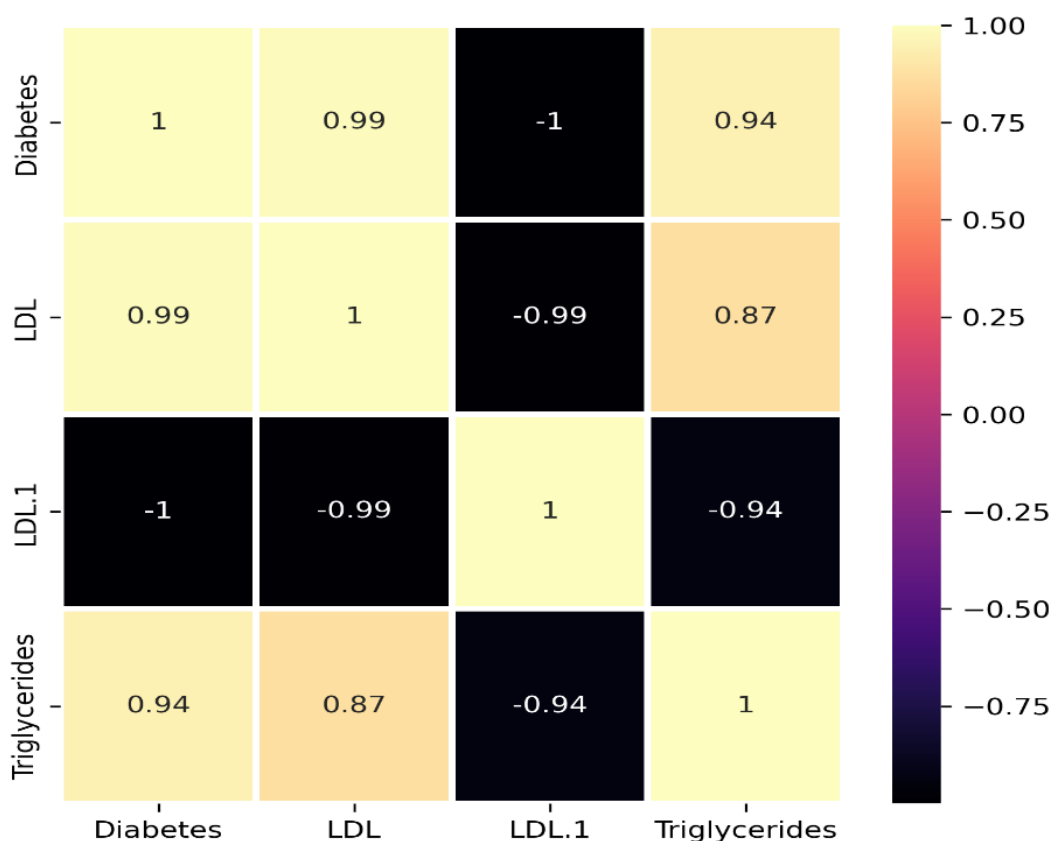


Fig. 2. Correlation heat map between the process parameters and the responses.

Figure 2 shows a correlation heat map illustrating the relationships between diabetes, LDL, LDL₁, and triglycerides. Strong positive and negative correlations are evident, for example the perfect negative correlation between LDL₁ and diabetes (-1.00), indicating the inverse behaviour. High correlation values indicate strong interdependence between variables, which is useful for predictive modelling.

3.2. Ada Boost Regression (Diabetes)

Figure 3 illustrates the performance of the Ada Boost regression model on the diabetes training data, highlighting its ability to capture complex, nonlinear relationships between features and target values. The plotted results show close alignment between predicted and actual values, indicating effective learning and strong model fit during the training phase. Figure 4 presents the performance of the Ada Boost regression model on the diabetes trial data, showing its predictive ability in unobserved samples. The scatterplot indicates a reasonable correlation between the predicted and actual values, albeit with slightly increased deviations, reflecting the generalizability of the model and potential areas for further improvement.

Table 3 evaluates Ada Boost Regression (ABR) in predicting diabetes-related outcomes, comparing training and testing performance. The training data shows almost perfect

model performance, with R^2 0.99880, explained variance score (EVS) 0.99880, and very low errors (MSE: 1.54, RMSE: 1.24, MAE: 0.86). However, the test metrics reveal a significant drop in accuracy (R^2 : 0.96686, EVS: 0.97400), with increased errors (MSE: 25.49, RMSE: 5.05, MAE: 4.22), indicating some over fitting.

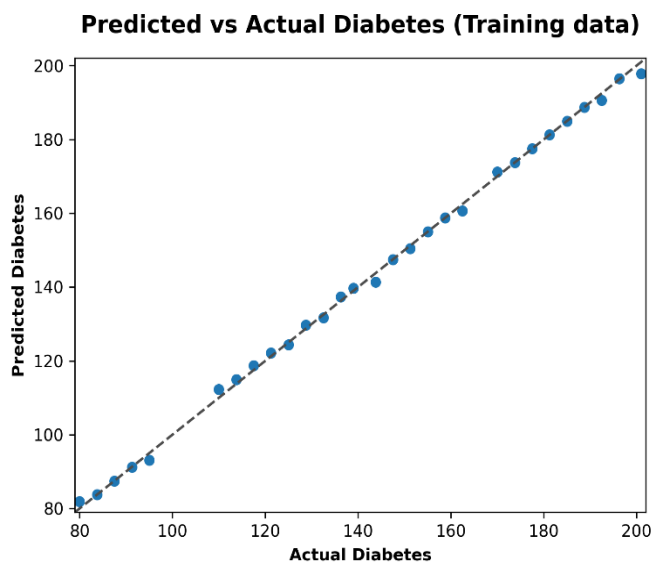


Fig. 3. Ada Boost Regression on Diabetes: training data.

The model generalizes reasonably well to unseen data, as evidenced by the even higher R^2 , while the larger testing errors suggest that predictions on new data may be less accurate than on training data. Max Error and Med AE increase in testing, reinforcing this trend. The ABR performs exceptionally well on training data, but shows slightly less reliability in real-world applications.

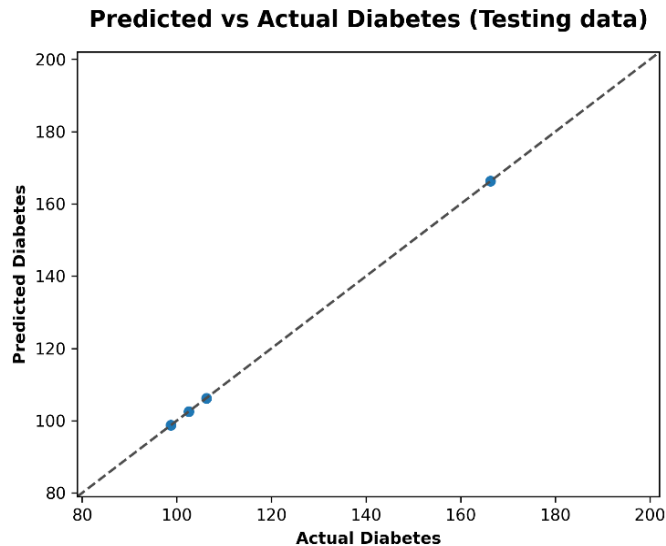


Fig. 4. Ada Boost Regression on Diabetes: testing data.

3.3. Ada Boost Regression (LDL.1 (HDL))

Figure 5 shows the performance of the Ada Boost regression model on the LDL.1 (HDL) training data, showing strong alignment between predicted and actual values. The scatterplot reflects the model's ability to effectively learn the underlying patterns within the dataset, indicating accurate fit and robust performance during the training phase with minimal prediction errors.

Figure 6 illustrates the performance of the Ada Boost regression model on the LDL.1 (HDL) test data, highlighting its predictive performance in unobserved samples. The scatterplot shows a reasonable fit between the predicted and actual values, with small deviations, indicating good generalization ability, while indicating potential for refinement to further improve the prediction accuracy.

Table 4 evaluates Ada Boost Regression (ABR) to predict HDL (labelled LDL.1) levels and compares training

and test performance. On the training data, this model demonstrates excellent accuracy with 0.99857 R^2 , 0.99857 explained variance score (EVS), and minimal errors (MSE: 1.04, RMSE: 1.02, MAE: 0.75). However, the test performance decreases (R^2 : 0.95672, EVS: 0.96347), with high errors (MSE: 21.11, RMSE: 4.59, MAE: 3.81), indicating moderate over fitting.

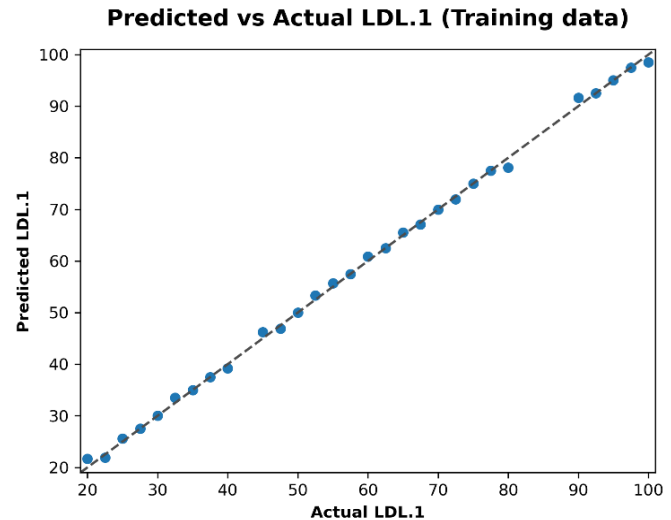


Fig. 5. Ada Boost Regression on LDL.1 (HDL): training data.

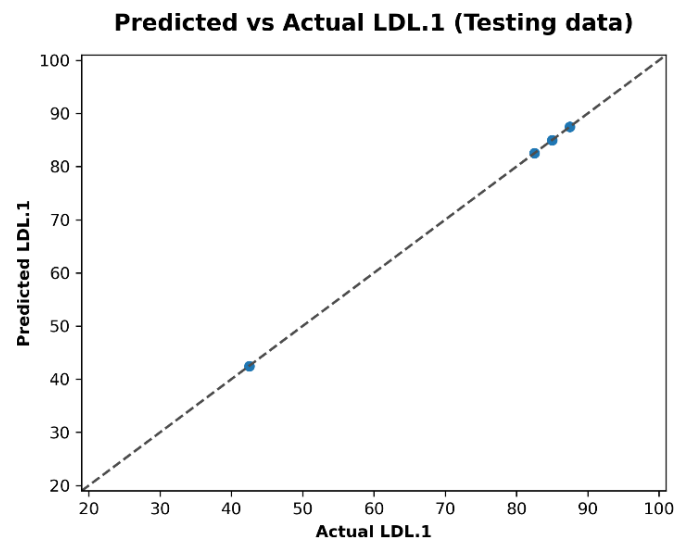


Fig. 6. Ada Boost Regression on LDL.1 (HDL): testing data.

Table 3. Performance Metrics of Ada Boost Regression on Diabetes (Training Data and Testing Data).

Property	Data	Symbol	Model	R^2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Diabetes	Train	ABR	Ada Boost Regression	0.99880	0.99880	1.53541	1.23912	0.86494	3.16667	0.00009	0.75000
	Test	ABR	Ada Boost Regression	0.96686	0.97400	25.48828	5.04859	4.21875	7.50000	0.00224	4.68750

Table 4. Performance Metrics of Ada Boost Regression on LDL.1 (HDL) (Training Data and Testing Data).

Property	Data	Symbol	Model		R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
LDL.1 (HDL)	Train	ABR	Ada Boost		0.99857	0.99857	1.03790	1.01877	0.74649	1.87500	0.00010	0.62167
	Test	ABR	Ada Boost		0.95672	0.96347	21.10800	4.59434	3.80969	7.50000	0.00230	3.75000

Table 5. Performance Metrics of Ada Boost Regression on LDL (Training Data and Testing Data).

Property	Data	Symbol	Model		R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
LDL	Train	ABR	Ada Boost		0.99888	0.99889	0.63384	0.79614	0.53517	1.87500	0.00038	0.50000
	Test	ABR	Ada Boost		0.95796	0.96492	14.36806	3.79052	3.62500	5.00000	0.00239	3.75000

3.4. Ada Boost Regression (LDL)

Max Error and Med AE increase significantly in the test, indicating that although ABR fits the training data almost perfectly, its predictive ability on the unobserved data is strong but less accurate. This method is consistent with typical machine learning trade-offs between training accuracy and generalization.

Figure 7 depicts the performance of the Ada Boost regression model on the LDL training data, showing a strong correlation between the predicted and actual values. The scatterplot indicates that it effectively learns the patterns of the dataset with minimal error, reflecting the robustness and high accuracy of the model during the training phase for LDL prediction tasks.

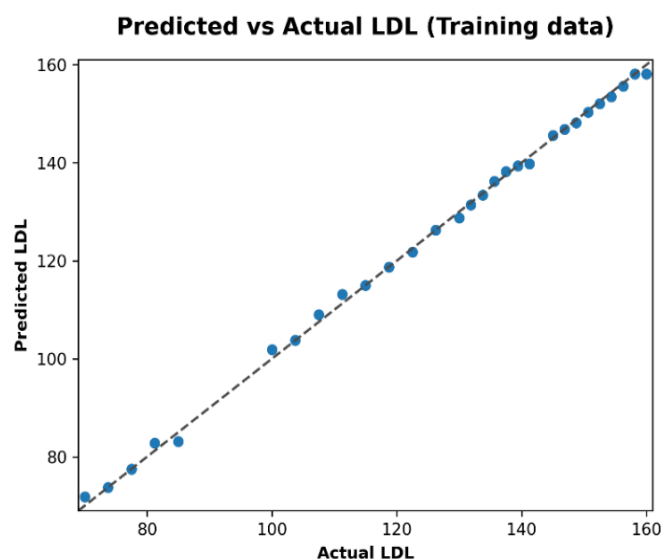
**Fig. 7.** Ada Boost Regression on LDL: training data.

Figure 8 presents the performance of the Ada Boost regression model on the LDL test data, demonstrating its predictive ability in unobserved observations. The scatterplot

reveals a good correlation between the predicted and actual values, with small deviations, indicating useful generalization while leaving room for further improvement in accuracy through parameter tuning or model refinement.

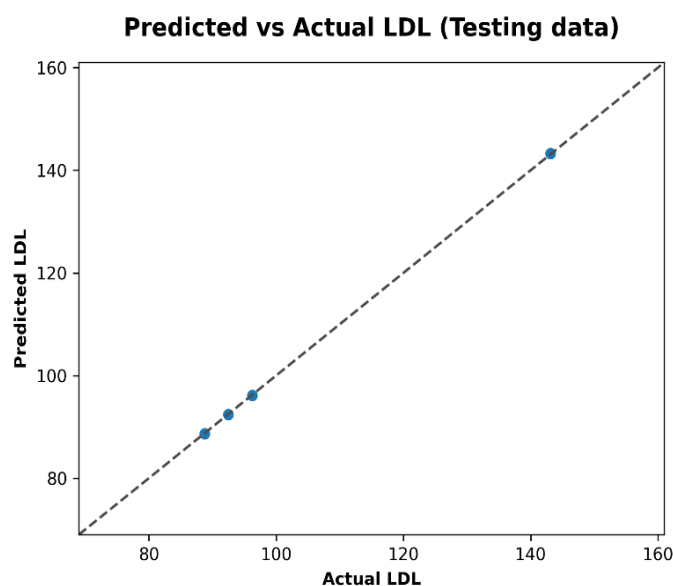
**Fig. 8.** Ada Boost Regression on LDL: testing data.

Table 5 evaluates Ada Boost Regression (ABR) for predicting LDL levels and compares training and testing performance. On the training data, this model achieves near-perfect accuracy with 0.99888 R^2 , 0.99889 explained variance score (EVS), and very low errors (MSE: 0.63, RMSE: 0.80, MAE: 0.54). However, the test data shows a decline in performance with higher errors (MSE: 14.37, RMSE: 3.79, MAE: 3.63) (R^2 : 0.95796, EVS: 0.96492), indicating some over fitting. Max Error and Med AE increase significantly in testing, indicating that while ABR performs exceptionally well on the training data, its generalization to unobserved data is good but not accurate.

3.5. Ada Boost Regression (Triglycerides)

Figure 9 illustrates the performance of the Ada Boost regression model on the triglycerides training data, showing a strong alignment between the predicted and actual values. The scatterplot reflects the model's ability to effectively learn the underlying relationships within the dataset, achieving high accuracy and strong fit with minimal errors during the training phase.

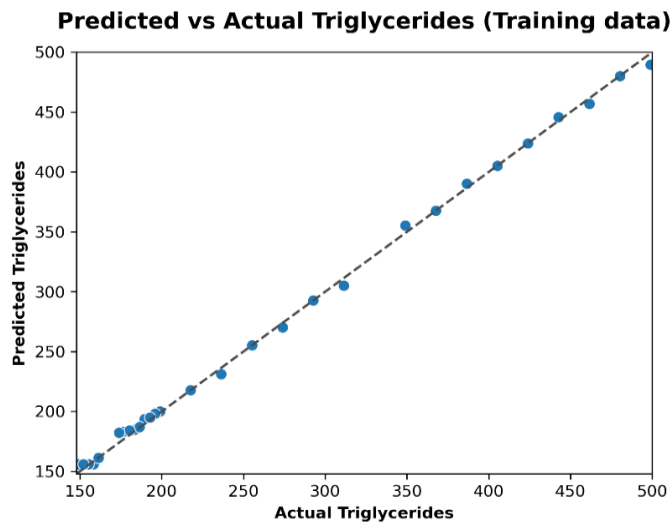


Fig. 9. Ada Boost Regression on Triglycerides: training data.

Figure 10 shows the performance of the Ada Boost regression model on the triglycerides test data, demonstrating its predictive power in unobserved samples. The scatterplot indicates a clear relationship between the predicted and actual values, with small deviations, indicating good generalization ability, while leaving room for further improvement to improve the prediction accuracy.

Table 6 presents the performance metrics of Ada Boost Regression (ABR) for predicting triglyceride levels estimated on both the training and test datasets. For the training data, the model shows exceptional performance with an R^2 of 0.9987, an explained variance score (EVS) of 0.99875, and very low errors (MSE: 16.62, RMSE: 4.08, MAE: 3.00). The test data, while still robust, shows slightly reduced performance with higher errors (MSE: 108.28, RMSE: 10.41, MAE: 8.28), indicating some over fitting. Max Error, MSLE, and Med AE also reflect this trend, with the test errors being large but still reasonable for prediction accuracy. Overall, ABR performs well, especially on the training data.

Predicted vs Actual Triglycerides (Testing data)

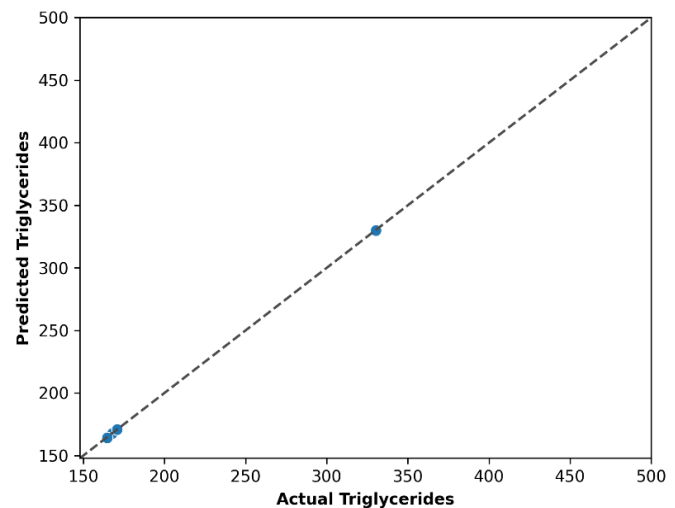


Fig. 10. Ada Boost Regression on Triglycerides: testing data.

4. CONCLUSION

Based on the detailed analysis presented in this study, quantum-enhanced machine learning (QuEML) represents a significant breakthrough in cardiovascular disease prediction, showing superior performance compared to conventional machine learning approaches. This research successfully validates the transformative potential of quantum-enhanced computer integration in clinical diagnosis through several novel architectures, including QCVNET, IQCNN, HQNN, and HRFQNN models. Experimental results firmly establish the superiority of quantum-enhanced approaches, with QCVNET achieving 91.73% accuracy in cardiovascular disease prediction, while QuEML models showed a consistent 0.6% improvement in accuracy over traditional methods. The computational efficiency gains are equally significant, with the training time reduced from 862.5 μ s to 670 μ s per cycle, representing a significant 22.3% improvement in processing speed. The 91% classification accuracy of the IQCNN framework, at a 70% learning rate, combined with exceptional AUC scores of 96.43% and 97.78%, underscore the robustness and reliability of quantum-enhanced frameworks. Integrating key physiological parameters, including diabetes indicators, LDL cholesterol, HDL cholesterol, and triglycerides, into the quantum framework enables comprehensive risk assessment with improved predictive capabilities.

Table 6. Ada Boost Regression Performance Metrics on Triglycerides (Training Data and Testing Data).

Property	Data	Symbol	Model	R^2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Triglycerides	Train	ABR	Ada Boost Regression	0.99870	0.99875	16.62447	4.07731	3.00390	9.37500	0.00033	2.34750
	Test	ABR	Ada Boost Regression	0.97815	0.99198	108.28240	10.40588	8.27925	18.75000	0.00144	6.24750

Comparative analysis against traditional approaches, including SVM, RF, RNN, DNN, Bi-LSTM, and CNN, consistently favoured the quantum-enhanced models across multiple performance metrics, including precision, recall, specificity, and F1-score. These findings position quantum-enhanced machine learning as a highly effective solution for cardiovascular risk assessment and early detection systems, providing substantial improvements in both accuracy and computational efficiency. Successful implementation of quantum computing principles in medical diagnostics opens new avenues for personalized healthcare and precision medicine. As cardiovascular diseases continue to be the leading cause of death worldwide, the adoption of quantum-enhanced prognostic methods could significantly impact patient outcomes through earlier detection, more accurate risk stratification, and the development of targeted therapeutic interventions, ultimately contributing to reducing mortality rates and improving the quality of life of patients worldwide.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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