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Quantum-Enhanced Machine Learning Algorithms for Heart Disease Prediction

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Abstract

Heart disease has grown more prominent among various age groups. Early prediction of heart failure and treating them with the most care can the human life. Today healthcare system depends on a computer-aided diagnosis system. Quantum improved machine learning approaches are a critical factor, play a significant role in healthcare systems due to their robust nature, and build novel medical traits, patient data, and management of patients' record and chronic disease detection, etc. Traditional machine learning approaches effectively predict heart disease but still lack efficiency due to noise and appropriate feature size. This informs the researchers to use quantum improved ML that will provide the accurate prediction of chronic diseases in a granular way. Applying these merits of quantum computing, healthcare systems are implementing quantum-based machine learning (QML) approaches for predicting heart disease. This paper proposes a quantum ML with quantum particle swarm optimization (QPSO) to predict heart disease and compare it with the traditional ML approach called multilayer perceptron (MLP) using the evaluation metrics. It uses exploratory preprocessing to normalize the input heart disease data. The number of qubits is the number of features in the dataset. The efficiency of the quantum-ML approaches is evaluated using publicly available heart disease dataset. The proposed QML with QPSO secured an improved accuracy of 96.7%, a false detection rate of 0.09, and a computation time is 135ms. However, the comparison results prove that QML with QPSO confirmed satisfactory results in predicting heart disease with improved accuracy.

Keywords

Quantum Computing, Machine Learning, Particle Swarm Optimization (PSO), Heart Disease, Quantum Machine Learning (QML), Multilayer Perceptron (MLP)

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1. Introduction

The advancement in digital technologies is leading the healthcare sector, while gaining much traction and positively contributing significantly. In many healthcare sectors, quantum-enhanced machine learning plays a significant role in developing innovative medical procedures, patient data monitoring, and maintaining an early diagnosis of chronic diseases. Quantum computing-based methods create effective medical administrative processes and treat chronic diseases.

Quantum-enhanced machine learning (ML) is the connection of quantum computing and ML which is used to inquire about how one area's research outcomes can be used to compute the other field issues. With the rapid increase in data usage, the current ML approaches are computationally low. In this sense, the quantum-enhanced ML offers compelling ML task advantages [1]. Quantum technology is divided into three categories such as quantum computing, quantum cryptography, and quantum information. Due to the generous permutations, quantum computing makes quantum computers work twice as fast with filling the qubit to fill up the memory [1]. Complex problems are solved using protein fold techniques and atom formation. Computer data in supercomputers are computed by multidimensional formation like protein folds in biological systems. This helps supercomputers solve the hardest supercomputer problems. Recent researchers focused on applying various ML approaches with quantum computing to produce efficient outcomes. Numerous works have been developed using artificial neural network (ANN) with quantum versions [2]. However, some authors have developed a quantum algorithm for pattern recognition issues [3]. In contrast, some authors developed a quantum-based system with traditional ML approaches. The quantum-enhanced ML approaches can also be used to solve some optimization problems too [4].

In recent years, researchers witnessed that there will be increased mortality and morbidity in the heart failure threat [5], and with the advanced technologies, the medical domain concentrate on detecting the heart failure threat, which changes patient health. Thus, the high mortality rate poses a challenge for healthcare providers. Heart failure is classified into biventricular, left ventricular, or right ventricular based on the affected location. Most of the research has found that female and older people suffer from heart failure with preserved ejection [6]. The major symptoms of heart failure include orthopnea, dyspnea shortness, pedal edema, lethargicness, tachycardia, S3 gallop, and jugular venous pressure [7].

The major advantage of using quantum computing is that it is super-fast and capable of solving complex problems. It can compensate for ML performance by making speedy decisions. This informs our research to use quantum techniques in predicting heart disease earlier. The qubits or quantum bits help to analyze possibilities of heart disease very fast and accurately when compared to binary bits in ML techniques. The major challenge of quantum ML is that designing the system is very difficult.

The traditional ML and quantum-enhanced ML approaches are used effectively in healthcare to aid patient health. This informs this research to use quantum in ML. Even though the ML and deep learning (DL) models have provided adequate results, the accuracy is lower due to the learning between input and output based on classical probability [8]. Hence, it warranted more improvements with general acceptability for heart disease prediction. Moreover, quantum machines are effective in different domains such as prediction, object detection and tracking, classification, and good performance on classical problems. The work [9] stated that quantum mechanics uplifts the ML and DL model performance. The quantum particle swarm optimization is used to diagnose diabetes in [10]. The quantum mean classifier is used for binary classification with optimal performance in [11]. To improve the ANN, quantum-inspired evolutionary approaches were used with a self-configuring nature based on the input data in [12]. The researchers used a rubidium-based quantum sensor [13] to detect arterial fibrillation, which is a disease that causes an abnormally high heartbeat.

Based on quantum computing, this paper denotes an interest in a new model for detecting heart disease. Under this umbrella of discussions, it is observed that traditional and quantum-enhanced ML approaches for the Internet of Medical Things provide earlier diagnoses of chronic diseases and predict their characteristics under various conditions. The contributions of the proposed work are as follows:

- Firstly, heart disease is predicted using the traditional ML method called multilayer perceptron (MLP).
- In parallel, preprocessed data is applied to the proposed quantum machine learning (QML) optimized with quantum particle swarm optimization (QPSO) for predicting heart disease on the collected data from the UCI Repository (https://archive.ics.uci.edu/).
- Both models are implemented with an optimal number of hidden layers, and the results are evaluated in terms of evaluation metrics.

The remaining section of this paper is organized as follows: Section 2 discusses the related work, followed by the proposed methods and dataset discussion in Section 3. Section 4 presents the experiments with the proposed and traditional models for heart prediction and compared their performance. Section 5 concludes the proposed model efficiency with a future direction of research.

2. Related Work

This section discusses the related work on heart disease prediction using quantum computing and ML approaches. Ur Rasool et al. [14] reviewed the quantum computing potential for healthcare systems undergoing transitions from a traditional healthcare system to a quantum-based one to reduce the computational overhead. They also addressed the critical requirement of quantum computing for healthcare providers and studied quantum cryptography in terms of identifying the security vulnerabilities in healthcare systems. Then they discussed the challenges, issues, and future research paths of quantum computing in the healthcare industry.

Gupta et al. [15] compared the deep learning and quantum machine learning models for diabetes prediction. The multilayer feed-forward perceptron and QML model have been evaluated and compared for evaluation metrics. They conclude that with an exploratory data preprocessing, the DL model secured improved accuracy in diabetes prediction than the quantum-based ML approach on the PIDD dataset.

Kumar et al. [16] discussed the quantum-enhanced ML approaches such as quantum random forest, quantum K-nearest neighbor (KNN), quantum decision tree, and quantum Gaussian naïve Bayes for heart failure prediction. They compared the quantum ML approaches on the heart disease dataset in terms of evaluation metrics, with an 89% accuracy being obtained by the quantum random forest classifier versus other approaches. Liu et al. [17] designed a logistic regression with novel QPSO for health examinations as to early detection of disease risk factors. They compared a common PSO and improved PSO and secured an 84.03% accuracy for a novel PSO versus a common PSO.

Hasan et al. [18] developed a heart disease diagnostic system using a MLP and support vector machine (SVM) using two datasets as data from the UCI Repository and database from Ibn Al-Bitar Hospital Cardia Surgery and Baghdad Medical City. The simulation results prove that MLP performs better with an accuracy of 98% than SVM. Paler et al. [19] developed a quantum approximate optimization approach to solve the optimization issues based on a positive integer, directly proportional to the approximation quality. Dang et al. [20] used quantum KNN for image classification, and secured an 83.1% accuracy on the Graz-01 dataset, and for the Caltech dataset, an 78% accuracy was obtained.

Ramisetty and Varma [2] developed a quantum convolutional neural network (QCNN) for error correction in multiscale entanglement and renormalization methods. In [21], the authors developed a quantum recurrent neural network in the research area of electroencephalography signals, described quantum autoregressive and quantum recurrent neural networks, and secured an accuracy of 88.28%. Wallach et al. [22] developed a quantum neural network with the properties of ANN with a quantum structure in big data for automated control systems.

Amin et al. [23] used a quantum neural network for coronavirus disease 2019 (COVID-19) analysis. They studied quantum and conventional ML methods and secured the precision, accuracy, recall, and F1-score as 0.94 on the POF dataset. For the UCSD-A14H dataset, quantum neural network ensured the precision, accuracy, memory, and F1-score as 0.96, 0.96, 0.95, and 0.96, respectively. Gupta et al. [15] built a predictive tool for diabetes prediction in the PIMA dataset and assisted physicians in reducing the mortality in diabetes patients. Gheisari and Esnaashari [24] investigated quantum dot synthesis, its basics, and application in the healthcare sector. Some of the QML-based healthcare platforms are PathAI, Enlitic, Freenome, BioXcel Therapeutics, BERG health, XtalPi, Atomwise, Deep Genomics, BenevolenAI, Olive, Qventus, Babylon Health, CloudMedX, Vicarious Surgical, Auris Health, Intuitive, and Microsure. Heart disease is monitored using the integrated ML technique in [25]. This approach uses only ML methods which need more accuracy in the system. The fuzzy model [26], wrapper ML [27] feature selection, and fusion algorithm [28] are used in analyzing heart-related data for the early prediction of heart disease.

3. Proposed Materials and Methods

This section discusses the information regarding heart disease prediction, such as dataset and traditional ML algorithms, and proposes a QML-based prediction system optimized by QPSO.

3.1 Dataset Description

The dataset used for the prediction of heart disease using traditional and QML approaches is collected from the UCI Repository (https://archive.ics.uci.edu), and consists of 304 instances and 14 attributes such as age, blood pressure, gender, cholesterol, ECG, blood sugar, and heart rate at a maximum and etc., which is shown in Table 1.

Table 1. Dataset description with its attributes

Attribute name	Description	Input type
_Age	Patients age	Years
_Sex	1 'male' and 0 'female'	Number
_trestbps	Resting blood pressure	Mm/Hg
_cp	Chest pain type: 1 'typical angina,' 2 'atypical angina,' 3 'nonanginal pain,' and 4 'asymptomatic'	Float
_Cholesterol	Serum cholesterol	Mg/dl
_fps	Fasting blood sugar >120 mg/dL where 1 'true' and 0 'false'	Float
_restecg	Resting electrocardiographic result, 0 'normal,' 1 'ST-T abnormality,' 2 'definite left ventricular hypertrophy'	Float
_thalach	Maximum heart rate	Binary
_exang	Exercise added angina	Int
_old peak	ST depression	Continuous
_slope	Peak exercise ST, value 1 'upsloping,' 2 'flat,' 3 'downsampling'	Float
_ca	Major vessels follow-up (0–3)	Float
_thal	Normal value '3,' fixed defect '6,' and reversible defect '7'	Float
_target	Whether a person suffered from heart disease, 0 'normal' suffering from heart disease	Float

The primary attribute that causes heart failure is age, which is considered a significant attribute. Heart failure patients aged 65 years and older are prone to heart disease. After the age of 55, there is a possibility of stroke in each decade interval, leading to heart-related issues [29, 30]. The following attribute is gender, where male patients are at higher risk of chronic diseases than females. Women with diabetes have a higher chance of heart disease than males. The following risk factor is chest pain (angina), which occurs when the oxygen-rich blood is not supplied to the heart. The heart disease patient may feel as if someone is squeezing their chest, and they also tend to suffer from pain in their shoulder, neck, back, arms, and jaw as well as indigestion.

The increasing value of serum cholesterol is the cause of collapsing arteries. The blood pressure also causes stress in the hearts, and blood pressure combined with high cholesterol, obesity, and diabetes lead to an increased risk of heart failure. While increasing triglycerides, cardiac arrest risk also increases. Increasing the rate of high-density lipoprotein will reduce the risk of heart attack [31, 32]. A blood sugar-level spike will cause heart failure where the pancreas does not generate happy hormones. The maximum value of cardiac rate is another risk factor for heart failure. Exercise-induced angina and ST-segment are other factors of heart failure. The treadmill electrocardiography (ECG) exercise records the pressure irregularly, while the depression of the ST-segment is higher or equal to 1 mm at 60 to 80 ms.

3.2 Proposed System Model

The overview of proposed heart disease prediction using traditional and QML-based approaches is shown in Fig. 1. The dataset is collected from the UCI Repository, and the details are discussed in Section 3.1. It is preprocessed to check the NULL values, while the string values are converted into numeric values since strings are not processed in ML algorithms. The standardization and data transformation are implemented using the Python library functions, with the values being scaled in the range. The preprocessing steps are used to improve the results.

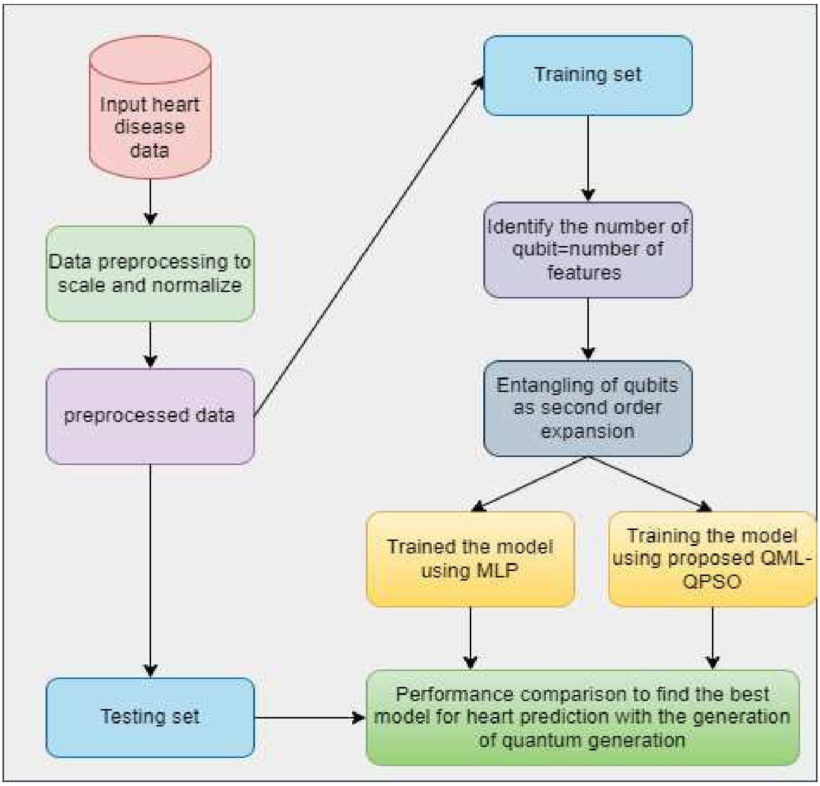

Fig 1. Overview of proposed QML-QPSO-based heart disease prediction.

Once preprocessing is over, the data are divided into testing and training sets in the ratio of 8:2. The proposed model is implemented in training data. The number of features corresponds to the number of qubits which is 14 for this study, and the mapping is performed as the second-order expansion of features. The MLP and QML algorithms are applied on preprocessed trained data and optimized with QPSO. The trained model is tested with testing data, and the performance of the algorithms is compared in terms of evaluation metrics of accuracy, recall, and precision F1-score.

3.2.1 Preprocessing

It is an essential step for data analysis and takes care of the imbalanced and duplicate data, low variance and highly correlated attributes, outliers, and missing values in the dataset. The considered heart disease dataset does not contain missing values. Therefore, the current preprocessing involves outlier removal and normalization of the dataset. The deviated features from the observations are treated as outliers, which must be removed from the dataset to improve the classifier performance. The outliers are detected and removed using quartiles as shown in Equation (1):

$$O_f = \begin{cases} f & if\ q_1 - 1.5 \times iq \leq f \leq q_3 + 1.5 \times iq \\ remove & otherwise \end{cases}, \tag{1}$$

where, f is feature vector occurrences that lie in n-dimensional feature space; q_1, q_2, q_3, and iq is first, second, third, and interquartile feature ranges, respectively. The normalization is performed by rescaling with the standard distribution and zero mean and variance as stated in Equation (2):

$$N(f) = \frac{f-\bar{f}}{\sigma}, \tag{2}$$

where, $\bar{f}$ is mean and σ is standard deviation.

3.2.2 Traditional ML algorithm (MLP)

MLP is a widely used supervised neural network for medical diagnosis, consisting of three or more layers such as input, hidden, and output layers. Input layers receive external inputs. In this work, the number of features is given as input followed by more than one hidden layer for processing and one output layer for classification results as shown in Fig. 2. The input layer consists of 13 features of the medical factors. The number of nodes in the hidden layer and its parameters are important factors and decided based on the experiments which led to better classification results. In this paper, three hidden layers were used each with five neurons. Two neurons are present in the output layer each indicating the patient's status as normal or abnormal.

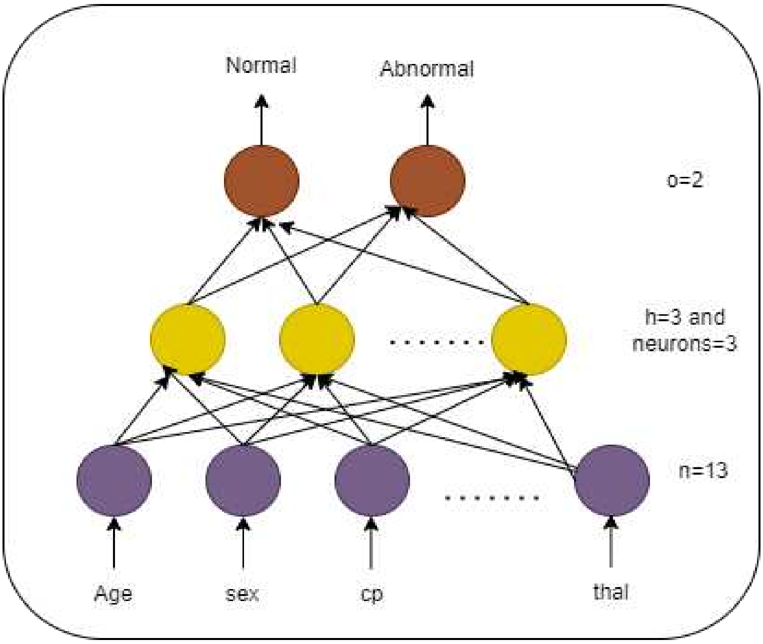

Fig. 2. MLP structure.

In the neural network, the data are accessed in the input layer and processed in the hidden layer until the output value is obtained which indicates the patient status as class results. The results may have a high value as the normal and low values for the remainder. The MLP node [33, 16] is structured as in Fig. 3 for calculating the weighted sum of the input with bias, and passes this sum via an activation function. These computation and activation functions are declared as shown in Equation (3), with the output obtained using Equation (4).

$$C_j = \sum_{i=1}^{p} w_{ji}.f_i + \theta_j, \tag{3}$$

$$y_j = a_j(C_j), \tag{4}$$

where, C is the linear combination of the inputs f_1, f_2,…f_p; θ_j is bias; w_{ji} is weight between input f_i and neuron j; a_j is activation function of neuron j; and y is output. Sigmoid activation function has been used as denoted in Equation (5):

$$a(\alpha) = \frac{1}{1+e^{-\alpha}}. \tag{5}$$

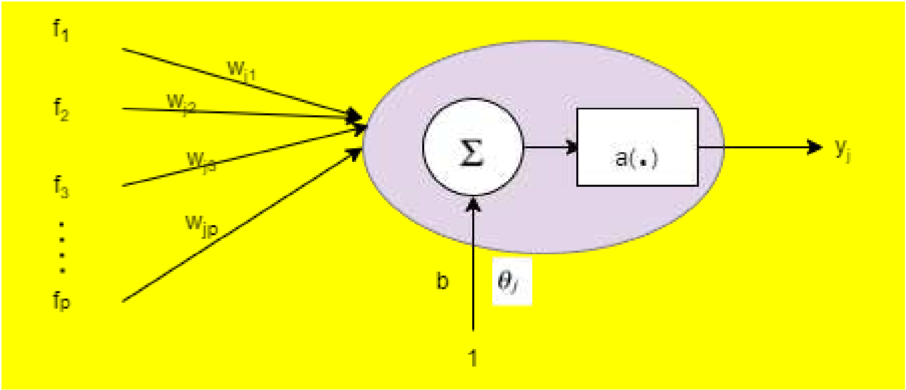

Fig. 3. MLP node.

The network consists of training and testing steps where the training phase updates the value of weight based on the supervised learning method called backpropagation algorithm as denoted in Equation (6):

$$w_{ji}(t+1) = w_{ji}(t) - \varepsilon \frac{\partial E_f}{\partial w_{ji}}(t), \tag{6}$$

where, ε is learning rate, E_f is error function (mean square error) between the desired output d, and actual output y as denoted in Equation (7):

$$E = \frac{1}{2}\sum_{j=1}^{N_j}(d_j - y_j)^2. \tag{7}$$

3.2.3 QML and QPSO

The ML algorithms lack efficiency due to the learning parameters being required more for training which leads to computational burden. Quantum computing [34–36] can resolve this issue effectively using the mechanics properties such as superposition, entanglement, and interference. With these properties, the basic unit of quantum called qubits is in multiple states in parallel called superposition, and despite being separated by larger distances they are extremely correlated according to what is called entanglement and interference which denote the bias towards the desired point. Hence, to obtain artificial intelligence more closely, quantum computing has been researched by the researcher potentially. The superposition property is defined as denoted in Equation (8):

$$|\chi> = \tau|0> +\rho|1>, \quad (8)$$

where, $|\chi>$ is state between 0 and 1; τ and ρ is complex numbers, where $|\tau|^2 + |\rho|^2 = 1$. The qubit remains the same state, and after that it will be either state 1 or 0 based on the probability of $|\tau|^2$ or $|\rho|^2$, respectively. The number of qubits is calculated as denoted in Equation (9), and for this work, it is given as 13.

$$n(q) = log_2(No.of.attributes). \quad (9)$$

This work uses a variation quantum circuit to tune the hyper-parameters and train the QML classifier for the prediction of heart disease. Here, the MLP neural network is used to encode and decode the features, and consists of three components, namely encoder, decoder, and evaluator. The encoder encodes the input data into quantum states, while the decoder is responsible to produce output state and the evaluator to compare the circuit output with its respective input labels. The input training data are modeled with the quantum gate with the QPSO optimized cost function as denoted in Equation (10):

$$L(f,y) = \sum_{j\neq y} \max(0, h_i - h_y + \Delta), \quad (10)$$

h_i is computed using Equation (11):

$$h_i = C_i(f;\alpha), \quad (11)$$

where, Δ is safe margin, h_i is interpreted score of classifier C on input f, where $h_i \in [-1,1]$. The parameters are tuned using the QPSO optimization approach with a learning rate of 0.001. The parameters of QML are listed in Table 2.

Table 2. QML parameters with their values

Number	Parameter	Value
1	Number of qubits	13
2	Number of CNOT gate	13
3	Number of qnodes	10
4	Batch size	10
5	Learning rate	0.001
6	Epochs	100
7	Safe margin	0.14

The QPSO has been used as global optimization due to its computational speed and involvement of less parameters. The particle swarm dimension is *X* for the *i*-th particle *P* is defined as:

$$Particle\ P_i = (P_{i1}, P_{i2}, ..P_{iX})$$

$$Particle\ speed\ S_i = S_{i1}, S_{i2}, ...S_{iX}$$

$$Global\ optimal\ particle\ gbest = (g_{i1}, g_{i2,...}g_{iX})$$

$$Local\ optimal\ particle\ lbest = (l_{i1}, l_{i2,...}l_{iX})$$

The particle renewal equation is defined as follows in Equations (12) and (13):

$$S_i(t+1) = w(t) \times S_i(t) + a_1 \times r_1 \times \left(lbest_i(t) - P_i(t)\right) + a_2 \times r_2 \times \left(gbest(t) - P_i(t)\right), \quad (12)$$

$$P_i(t+1) = P_i(t) + S_i(t+1), \tag{13}$$

where, t is the iteration; a_1 and a_2 are acceleration factor such that a_1=a_2=2; r_1 and r_1 are random numbers with the interval (0, 1); and $w(t)$ is an iteration weight as denoted in Equation (14):

$$w(t) = w_{max} - \frac{(w_{max} - w_{min}) \times t}{t_{max}}, \tag{14}$$

where, w_{max} is maximum range of w with the value of 1.3, w_{min} is minimum range of w with the value of 0.3, and t_{max} is maximum iteration. The speed and particle positions are computed based on logistic mapping. The random number r for the iteration $(t + 1)$ is generated as denoted in Equation (15):

$$r(t+1) = \mathrm{C} \times r(t).(1 - r(t)), \tag{15}$$

where, $r \in [0,1]$ and C is control variable where $\mathrm{C} = 3$. The workflow of the proposed QML-PSO based heart disease prediction is shown in Fig. 4. The steps involved in QPSO are as follows:

Step 1: The particle speed, position, population, acceleration coefficient, and maximum iteration are initialized.
Step 2: Update the position and speed to find best fitness value using Equation (13).
Step 3: Using various speeds and directions, optimize the particle at each phase.
Step 4: Set i = 0 where more than the total number of particles and go to step 5, otherwise i = i + 1 and go to step 3.
Step 5: After the error exceeds the rule, terminate the execution.

The traditional ML approach called MLP and proposed QML with QPSO is evaluated, and the best results are obtained by QML with QPSO, which will provide accurate heart disease prediction with a minimum false prediction rate.

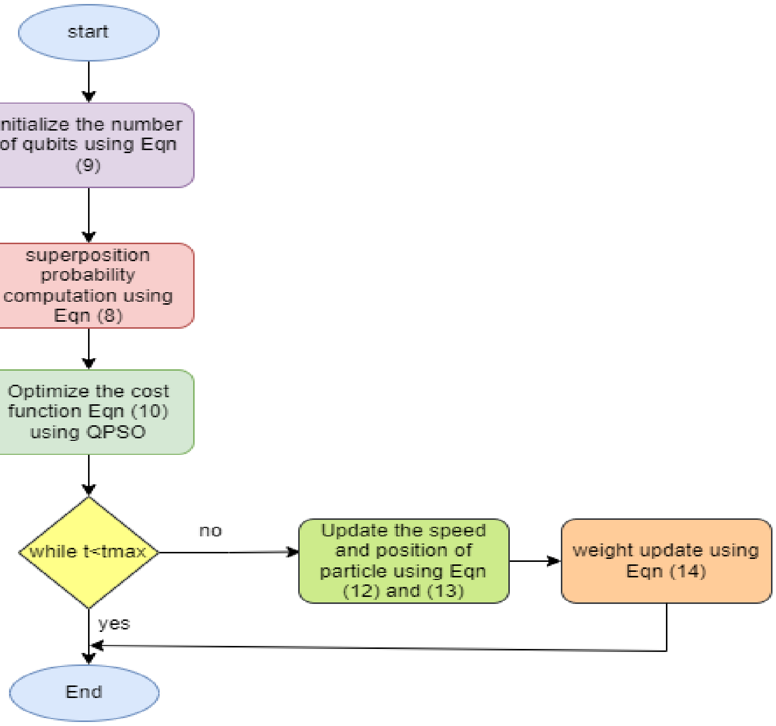

Fig. 4. Workflow of proposed QML-QPSO-based heart disease prediction.

4. Experimental Results and Discussions

The proposed model has been implemented using a Python programming environment with various APIs of Python. This section discusses the evaluated results and their comparison to show the proposed model's performance in predicting heart disease.

4.1 Evaluation Metrics

The performances of the proposed and traditional ML-based heart failure detections are evaluated and compared in terms of accuracy, F1-score, recall, and precision [29, 30], as well as false detection rate, missed detection rate, and diagnostic odd ratio (DOR) [31, 32] denoted in Equation (16):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \tag{16}$$

where, TP, TN, FP, and FN represent the number of true positive, true negative, false positive, and false negatives, respectively. The better classifier secured true positive and true negative rates nearer to 100%. The next measure is F1-score or F-measure given as the ratio between accuracy and review as denoted in Equations (17) and (18):

$$F1-score = \frac{TP}{TP+1/2(FP+FN)}, \tag{17}$$

$$Recall = \frac{TP}{TP+FN}. \tag{18}$$

Recall is measured as the portion of a recovered sample among the important sample occurrences. For no recall, the measure value is 0 and for full recall, the measured value will be 1. Precision is measured as the significant samples among the recovered occasions denoted in Equation (19) below, with other metrics being measured through Equations (20)–(24):

$$Precision = \frac{TP}{TP+FP}, \tag{19}$$

$$Specificity = \frac{TN}{TN+FP}, \tag{20}$$

$$Balanced\ Accuracy = \frac{1}{2}(Recall + Specificity), \tag{21}$$

$$False\ detection\ rate\ (FDR) = \frac{FP}{TP+TN}, \tag{22}$$

$$Missed\ detection\ rate\ (MDR) = \frac{FN}{TP+TN}, \tag{23}$$

$$Diagnostic\ odd\ ratio\ (DOR) = \frac{TP+TN}{FP+FN}. \tag{24}$$

4.2 Performance Evaluation

This subsection illustrates and discusses about the evaluation preprocessing, MLP and QML with QPSO model for heart disease prediction.

4.2.1 Preprocessing results

The class-wise distribution of considered dataset features represents the identification of positive and negative samples. The outliers in the dataset may affect the model and lead to over or underestimation of the predicted results. After outlier removal, the number of pieces is reduced from 304 to 294, with the results of outlier removal being shown in Table 3. The preprocessed dataset is divided into training and test datasets for evaluation in the following sections.

Table 3. QML parameters with their values (results after outlier removal)

Feature#	Original			Values		
	Mean	Median	Std	Mean	Median	Std
1	32.12	28	10.75	32.81	29	11.03
2	121.30	113	31.93	119.67	113	29.08
3	67.34	71	18.82	68.28	71.2	11.87
4	69.45	73	19.67	68.03	72	12.34
5	124.21	102.3	29.23	121.4	102	27.81
6	4.43	4	4.41	4.4	4	4.26
7	35.32	29	11.56	34.56	29	11.1
8	65.38	68	19.23	64.31	65	18.34
9	101.45	98.21	31.43	100.28	98	30.82
10	33.45	27	10.76	33.56	28	10.72
11	0.45	0.36	0.33	0.41	0.359	0.27
12	75.65	36	8.62	62.43	35.4	15.35
13	38.388	26	11.45	36.91	25.7	10.32

4.2.2 Evaluation of traditional ML (MLP) model-based heart prediction

The performance of the traditional ML algorithm called MLP is evaluated in terms of the evaluation metrics. It is affected by its parameter training and learning of neurons, which will affect the complexity and not produce the optimal result.

The metrics are increased as a result of preprocessing and optimization. Table 4 represents the evaluated results of MLP through preprocessing and preprocessing with optimization. It is observed that MLP performs better with preprocessing and QPSO-based optimization. The original model based on MLP alone secured an accuracy of 67%. Varying outlier removal and normalization, it increased to 85%. Further, this model is optimized using QPSO for weight adjustment, increasing the accuracy rate to 91%. Hence, the ML model with preprocessing and QPSO will increase the accuracy and other metrics on the prediction of heart disease, and gradually reduce the false detection and missed detection rate.

Table 4. Developed MLP model under preprocessing and optimization process

Metrics	Original	With preprocessing	With QPSO
Accuracy	0.67	0.85	0.91
Precision	0.62	0.71	0.78
Recall	0.68	0.78	0.87
F1-score	0.65	0.74	0.82
Specificity	0.78	0.82	0.89
Balanced accuracy	0.73	0.8	0.88
FDR	0.16	0.14	0.12
MDR	0.14	0.08	0.05
DOR	35.67	74.72	78.98

4.2.3 Evaluation of proposed QML-QPSO model-based heart prediction

The performance of the proposed QML with QPSO is evaluated in terms of the evaluation metrics, and is affected by its parameter training and learning of neurons, which will affect the complexity and not produce the optimal result. Table 5 represents the evaluated results of QML-QPSO through preprocessing and preprocessing with optimization. It is observed that QML performs better with preprocessing and QPSO-based optimization. The metrics are increased and outperformed as a result of preprocessing and optimization. The original model is QML alone secured an accuracy of 87%. Varying outlier removal and normalization, it increased to 93%. Further, this model is optimized using QPSO for weight adjustment, increasing the accuracy rate to 96.7%. Hence, the QML model with preprocessing and QPSO will increase the accuracy and other metrics for predicting heart disease, and gradually reduce the false detection rate to 0.09 and missed detection rate to 0.03.

Table 5. Developed QML model under preprocessing and optimization process

Metrics	Original	With preprocessing	With QPSO
Accuracy	0.87	0.93	0.967
Precision	0.81	0.86	0.89
Recall	0.79	0.85	0.88
F1-score	0.86	0.88	0.891
Specificity	0.82	0.86	0.89
Balanced accuracy	0.81	0.86	0.89
FDR	0.12	0.11	0.09
MDR	0.09	0.07	0.03
DOR	71.3	75.64	84.53

4.2.4 Comparative evaluation of state-of-the-art methods

The traditional MLP and QML with QPSO-based heart disease prediction models are compared to prove their performance, and the results are shown in Figs. 5 and 6 in terms of the evaluation metrics. Both models performed their preprocessing, such as outlier removal and normalization before classification and optimization, which is applied to both models for weight and cost function updation. The traditional MLP for heart disease prediction secured the metrics, namely accuracy, precision, recall, F1-score, specificity, balanced accuracy, DOR, FDR, MDR, and computation time as 91%, 78%, 87%, 82%, 89%, 88%, 78%, 0.12, 0.05, and 194 ms, respectively. Alternatively, the proposed QML based heart disease prediction system secured the metrics, namely accuracy, precision, recall, F1-score, specificity, balanced accuracy, DOR, FDR, MDR, and computation time as 96.7%, 89%, 88%, 89%, 89%, 89%, 84%, 0.09, 0.03, and 135 ms, respectively. This result proves that the proposed model outperformed MLP and is efficient in predicting heart disease.

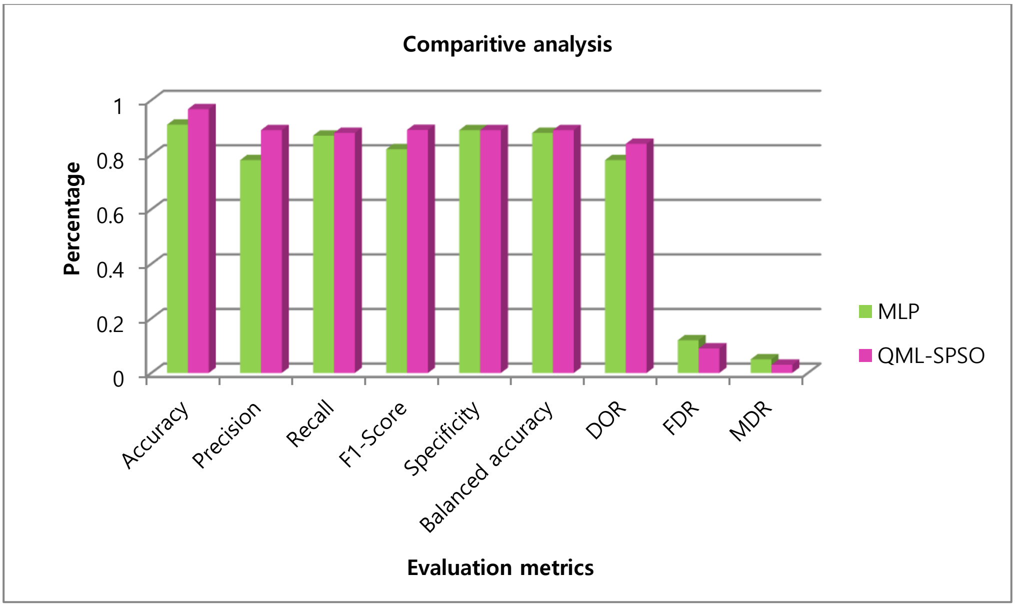

Fig. 5. Comparative analysis of MLP and QML-QPSO on heart disease prediction.

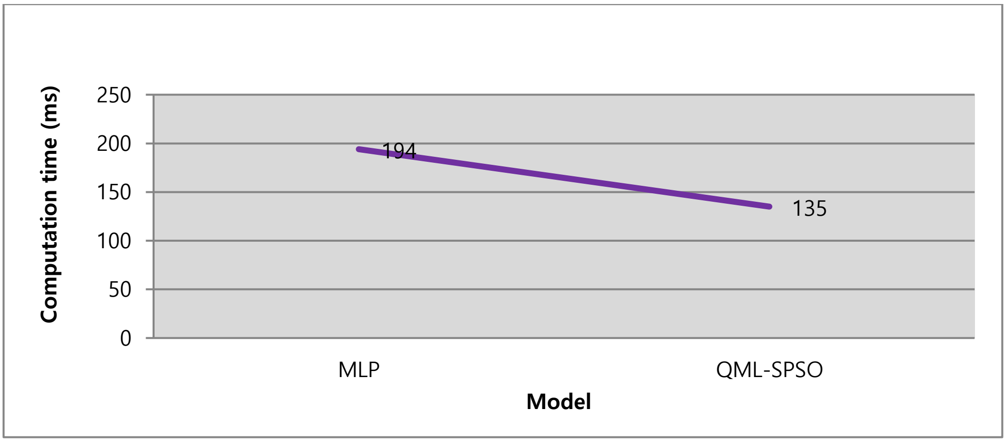

Fig. 6. Computation time comparison of MLP and QML-QPSO.

The efficiency and the performance of the proposed quantum computing-based model are compared with the state-of-the-art methods offered by Kavitha and Kaulgud [37], Mohan et al. [38], Kumar et al. [16], and Leema et al. [39], with the results being shown in Table 6. Compared to the approaches, the proposed QML-QPSO secured improved value of the evaluated metrics and performed superior to all other methods. Hence, all the evaluation results show the effectiveness and efficiency of the proposed QML-QPSO-based heart disease prediction as being beneficial for medical diagnosis.

Table 6. Comparative analysis of state-of-the-art methods with proposed model

Metrics	Kavitha and Kaulgud [37]	Mohan et al. [38]	Kumar et al. [16]	Leema et al. [39]	Proposed model
Accuracy	0.86	0.87	0.89	0.91	0.967
Precision	0.72	0.81	0.83	0.84	0.89
Recall	0.73	0.83	0.86	0.84	0.88
F1-score	0.73	0.78	0.84	0.86	0.891
Specificity	0.73	0.8	0.85	0.85	0.89
Balanced accuracy	0.73	0.82	0.86	0.85	0.89
FDR	0.12	0.11	0.13	0.1	0.09
MDR	0.07	0.06	0.06	0.067	0.03
DOR	0.78	0.82	0.81	0.83	0.84
Computation time (ms)	193	189	175	186	135

5. Conclusion

This paper study differences between prediction performance of ML and quantum-based ML techniques. The MLP and QML computes preprocessed data, and the prediction results are optimized with QPSO to improve the accuracy. The result evaluation shows that the MLP algorithm achieved an accuracy of 91% and QML assured an accuracy of 96.7%. Additional evaluation metrics, namely precision, recall, F1-score, specificity, balanced accuracy, DOR, FDR, MDR and computation time are shown with adequate performance for the quantum-based ML method compared to the traditional MLP. The proposed model is further compared with other state-of-the-art methods. The analysis shows that the developed QML model performance is superior to all other models in predicting heart disease. Hence, the proposed QML-QPSO model consumes less time to predict any heart problems. In the future, the QML model will be enhanced with exploratory analysis based on preprocessing of various large datasets of heart disease to examine the system's robustness. This quantum computing is considered as an adequate, user-friendly model for web-based applications. Also, quantum analysis can be computed in deep learning algorithms in future research.

Author's Contributions

Conceptualization: SSA, HAM; funding acquisition: SA; investigation and methodology: MAA, AM; project administration: AMA; resources: R.M.; supervision: SA; writing of the original draft: MAA, SSA: writing of the review and editing: SA, MAA, R,M; software, validation: MAA, AM; formal analysis: SSA, R.M; data curation, visualization: MAA, S.A. All the authors have proofread the final version.

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Competing Interests

The authors declare that they have no competing interests.

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