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Heart Failure Detection Using Instance Quantum Circuit Approach and Traditional Predictive Analysis

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Abstract: The earlier prediction of heart diseases and appropriate treatment are important for preventing cardiac failure complications and reducing the mortality rate. The traditional prediction and classification approaches have resulted in a minimum rate of prediction accuracy and hence to overcome the pitfalls in existing systems, the present research is aimed to perform the prediction of heart diseases with quantum learning. When quantum learning is employed in ML (Machine Learning) and DL (Deep Learning) algorithms, complex data can be performed efficiently with less time and a higher accuracy rate. Moreover, the proposed ML and DL algorithms possess the ability to adapt to predictions with alterations in the dataset integrated with quantum computing that provides robustness in the earlier detection of chronic diseases. The Cleveland heart disease dataset is being pre-processed for the checking of missing values to avoid incorrect predictions and also for improvising the rate of accuracy. Further, SVM (Support Vector Machine), DT (Decision Tree) and RF (Random Forest) are used to perform classification. Finally, disease prediction is performed with the proposed instance-based quantum ML and DL method in which the number of qubits is computed with respect to features and optimized with instance-based learning. Additionally, a comparative assessment is provided for quantifying the differences between the standard classification algorithms with quantum-based learning in order to determine the significance of quantum-based detection in heart failure. From the results, the accuracy of the proposed system using instance-based quantum DL and instance-based quantum ML is found to be 98% and 83.6% respectively.

Keywords: machine learning; deep learning; quantum computation; qubit; support vector machine; decision tree and random forest

MSC: 68Txx; 68Q09

Citation: Alsubai, S.; Alqahtani, A.; Binbusayyis, A.; Sha, M.; Gumaei, A.; Wang, S. Heart Failure Detection Using Instance Quantum Circuit Approach and Traditional Predictive Analysis. *Mathematics* **2023**, *11*, 1467. https://doi.org/10.3390/math11061467

Academic Editors: Frank Phillipson, Sebastian Feld, Matthias Möller, Ward van der Schoot and Niels Neumann

Received: 15 February 2023
Revised: 3 March 2023
Accepted: 13 March 2023
Published: 17 March 2023

1. Introduction

Heart Disease is considered to be one of the significant causes of death and early detection assist in mitigating the mortality rate considerably [1]. The complexities in data and correlations that occur during prediction are challenging tasks in traditional approaches. Historical medical information has been utilized for predicting the disease with the numerous traditional ML and DL approaches [2]. Similarly, the recommended research [3] has utilized three different supervised learning algorithms such as support vector machine (SVM), Naïve Bayes (NB) and decision tree (DT) for the exploration of correlations in heart disease data which have assisted in the enhancement of prediction. This considered approach has used the African heart disease dataset with a total of 462 instances and smart systems have performed a 10-fold cross-validation [4]. The real-time monitoring of patients with smart devices reduces the progress of the disease. However, the lack of effective data streaming and processing with the huge amount of real-time data has experienced difficulty with the need for appropriate timely diagnosis. The suggested approach [5] has used a 5 G-enabled monitoring mechanism in which the Flink-based streaming of data computation framework has been applied for accessing electrocardiography (ECG) data [6]. It also has been assisted with convolutional neural networks (CNN) and long short term memory) (LSTM) for obtaining automatic prediction of patient health [7].

The difficult blood circulation due to the build up of plaque within arteries is required to be detected at an earlier stage for avoiding serious progression. The considered research [8] has provided the DL technique with a stacked-sparse auto-encoder for achieving effective feature learning. The network consisted of multiple forms of autoencoders and also with softmax-based classifiers. In addition to that, the parameters of the algorithm have been optimized for enhanced performance [9]. Particle swarm optimization (PSO) is the computational method used for tuning the parameters of the stacked encoder. The optimization of the algorithm has been improved with the classification undertaken with smart encoders. The multiple-layer frameworks have led to an internal covariate mechanism which impacts the generalization capability. The process of batch normalization has been utilized for preventing complications. The accuracy has been improved with the experimental evaluations with ML in healthcare particularly in enhancing the time factor in diagnosis. The heart disease prediction in health care data with the utilization of ML algorithm has analysed vast amounts of patient data for attaining significant information in making decisions for prevention accordingly. To this purpose, the recommended study in [10] has developed a multilayer perceptron (MLP) training method for detection and performance evaluation findings have inferred that the diagnosis has been performed effectively with prediction accuracy. ML has the advantage of predicting outcomes based on previous data. The system holds the capacity of predicting the patterns from existing data and then it applies the inferred knowledge to the unknown dataset for the prediction of the outcome. Classification is considered to be a powerful mechanism in ML techniques utilized for prediction. Certain mechanisms have attained satisfactory accuracy while others have limited accuracy. For enhancing the accuracy of the weaker algorithms, the suggested research [11] has used ensemble-based classification with numerous classifiers. Its utility in the prediction of the disease at an earlier stage and satisfactory performance has been obtained in the identification of the risk of the disease. Ensemble mechanisms such as boosting and bagging are a significant improvement in prediction [12]. In order to achieve better performance with the traditional medical decision support mechanisms, the considered research [13] has designed a classifier-based ensemble model based on a bagging strategy with the multiple-weighted voting method for cardiac disease prediction. The integration of five different classifiers such as linear regression, instance-based learning mechanisms, SVM, discriminant analysis and NB with various datasets for experimentation and validation of the system. The datasets have been acquired from repositories. The prediction results have been assessed with the analysis of variance (ANOVA) based on statistical analysis and 10-fold cross-validation. The analysis has achieved improved accuracy in diagnosis with different types of attributes. ML and DL are considered to be effective methodologies for solving real-time problems. In addition to this, quantum-based networks have been arriving for enhancing the prediction accuracy of diseases with healthcare data. quantum neural networks have contained data from natural quantum systems or smart systems. The relation between the attributes in determining the disease has performed better with the quantum ML. The suggested technique in [14] has analysed the symptoms of the disease QML which has been identified with higher accuracy. The identification of the relation in disease occurrence is high through the suggested approach.

The Neural Network (NN) based classification with the convolutional layers has significantly differentiated the imbalanced medical data classes. The information has been gathered from the Nutritional and Health Examination database for the prediction of heart disease existence [15]. Even after adjustments made with weights, the traditional mechanisms have found difficulty with the vulnerability of data. The recommended research [16] has designed a simpler double-layer CNN which has exhibited resilience to the unbalancing data classes. Due to the increased scalability of the dataset with unbalanced data, it is challenging for acquiring a higher rate of prediction with true 1 and false 0 accuracy. In the first layer of implementation, assessment with feature-weights using least absolute shrinkage and selection operator (LASSO) [17]. It has performed a voting method for the identification of significant features which has been homogenized with the fully-connected layer. This process iteration has repeated for every feature for the successive stages of convolution. The training process per epoch with simulated annealing has been initiated for boosting the accuracy in classification. Despite the imbalanced data features in the dataset, the presence and absence of heart disease have been classified through testing and validation of the data [18]. Even though conventional studies have provided many methodologies and techniques for the earlier prediction of heart diseases in order to mitigate the rate of mortality, accuracy enhancement is still required in medical therapies for the early recovery of patients. Moreover, the identification of disease alone has not assisted clinicians in taking decisions, classification of patients with and without heart disease accurately demands effective algorithms to aid in clinical therapies. For this purpose, instance-based quantum ML and DL algorithms are being utilized in the present research for enhancing accuracy. Most of the existing studies have used binary classifications and they possess several drawbacks such as lesser accuracy, time-consuming and possess difficulties in performing complex data. In the present study, instance-based quantum ML and DL methods have been used to obtain promising results with improved accuracy. The proposed method has wider applications in the area of quantum computing, especially in data classification and prediction. The foremost intention of the proposed study is to address the challenges in the existing studies while attaining effective prediction of heart diseases. Based on the analysis made from various approaches, the aim and objective of the present system are being framed as follows:

- To predict heart disease with the data of the patients collected from the Cleveland heart dataset and performs pre-processing.
- To perform classification with the SVM, DT and RF and prediction accuracy for algorithms is computed individually.
- To execute a classification of diseases with the implementation of instance quantum-based ML and DL algorithms and validated the accuracy level of the system.
- To evaluate the effective classification algorithms through comparison of performance metrics such as accuracy, precision, recall and f-score for exhibiting the effectiveness of the proposed model.

In addition to the above, the present study offers a wide range of knowledge regarding instance-based quantum-enhanced ML and DL algorithms; instance-based quantum ML and DL algorithms have been used for the classification of heart diseases to improve the accuracy rate.

In the big-data era, huge data amounts arrive from various sources. A stage may be reached when supercomputers can be overwhelmed with big data. In this situation, training the neural network is a complex undertaking due to the dimension and size of big data. In addition, several parameters have to be utilized and optimized in a network for learning the patterns, thereby, assessing the data. To resolve this issue, quantum computing has evolved as an active research area as the quantum computer could represent data in various forms with qubits. The qubits on the quantum computers could be employed for detecting hidden data patterns that are complex for a traditional computer to find. Hence, considering the innate merits of quantum computing, this study has intended to make use of quantum based ML and DL for heart failure detection. In the proposed work, quantum ML and DL utilized quantum gates as well as the operations which seem to differ from traditional ML. Quantum computing also possesses the potential for providing faster speeds to ML and DL algorithms concerning search problems and large-scale optimization. Moreover, q quantum ML and DL algorithms are typically more scalable than conventional ML algorithms by using complex features. Overall, quantum-based ML and DL possess benefits such as improved runtime, better learning and capacity. Moreover, the study has considered the use of instance-based quantum based as it possesses the capability for adapting its model to unseen data. These advantages have motivated the present study to consider this approach as a novelty of the study.

The proposed research paper is organized as follows. Section 2 shows the review made on several existing studies related to the prediction of heart diseases through various ML and DL techniques. Section 3 outlines the proposed prediction analysis with the classification algorithm utilized in the study. Section 4 provides performance analysis and internal comparative assessment with other algorithms. Finally, the proposed work is concluded in Section 5.

2. Literature Review

The following section discusses the various methods and algorithms utilized in the prediction of heart-related irregularities [19] and the earlier techniques of assessing the heart disease diagnosis to assist in lowering the risk of progression. The suggested method [20] has constructed a hybrid technique based on DL for finding out whether a person has been affected by cardiac disease using CNN with Bi-LSTM. It has solved the complications of imbalanced and missed data values in a dataset with the utilization of data processing methodology. It also has used additional tree-based classifiers for the process of feature selection and classification [21]. The expected accuracy has been achieved through analysis with performance metrics such as precision, recall, f-score and accuracy. The dynamic detection framework has been handled with multiple periodic data with various intervals and larger-scale patient records have been effectively utilized for improving the performance of the considered system [22]. The LSTM structure for the prediction of the disease has utilized irregular time intervals which have been smoothed for obtaining the time parameterized vector which has been utilized for the input for the forget gate of LSTM which has overcome the prediction difficulties [23]. The experimental evaluations have shown classification outcomes with the smoothing-based irregular periodical time within various stages in medical diagnosis for obtaining a temporal-based feature vector. The DL architecture has exhibited a development as the investigative tool for enhanced clinical treatment and lower level of diagnosis cost with the incorporation of smart medical care systems.

The leading root cause behind mortality due to cardiac ailments has been primarily due to the delayed detection of illness and also by improper diagnosis [24]. Failure in the heart has to be accurately classified through effective training and fine-tuning of parameters in algorithms [25]. Several intelligent mechanisms developed for the automatic detection of cardiac failures have faced the over-fitting issue which drastically affects the accuracy of the system. The suggested methodology [26] has compromised accuracy performance on both testing and training data. The considered diagnostic strategy has utilized a random search technique for the selection of appropriate features in the prediction of the disease. The algorithm has been optimized using the grid-search method. The precision metric has been evaluated using two kinds of experiments [27]. The first experimentation has been performed with the RF model and the second one applied a random searching process to the RF model and has tested over with the Cleveland dataset. The complexity has been observed to be lower and has achieved higher accuracy compared to the traditional method. Eleven different algorithms have been compared for determining the efficacy of the system [28].

Medical practices are involved with the collection of various kinds of patient data which has helped clinicians in the proper diagnosis of the health status of patients [29]. Such health information has been provided with the symptoms detected from patients and primary diagnosis performed by the physicians along with the detailed laboratory results which could assist in the prediction of cardiac irregularities [30]. Such data has been utilized for analysis in confirming the disease by expert doctors. The accurate identification and classification have been done with the suggested research [31] with the deployment of

AI-based algorithms such as NB and RF classification algorithms to classify whether the patient has been affected or not [32]. The simulation outcome obtained from the comparison performed on two algorithms has exhibited efficiency even with the complex nature of the dataset taken from the online repositories. The recommended study [33] has utilized the UCI heart disease-based dataset with the voting-based mechanism for enhancement of the classifiers. Though ML tools are effective in analysing the huge volume of a dataset, they also contain irrelevant and redundant features which drastically affect the accuracy in classification and computational speed. The considered research [34] has utilized a feature selection process for the elimination of unrelated and unwanted data features. The wrapper-based feature selection mechanism has determined the optimal subset in the diagnosis of heart-related diseases. It has performed prediction with grey wolf optimization (GWO) for the selection of the best features from the dataset [35]. Moreover, the fitness of the algorithm has been evaluated with the utilization of an SVM classifier, Cleveland dataset has been taken for validating the system performance in which the prediction rate is satisfactory compared to other existing techniques [36].

The process of data mining has been effectively applied in the suggested medical analysis. The pre-processing method has eliminated the correlated columns and filled the data with the missing values [37]. An equal level of accuracy has been observed from the two types of classifiers applied to the dataset [38]. Identification of cardiac problems is included blood vessel blockages and contractions in the heart [39]. It affects both children and adults of all ages. The algorithms used for detection have to be intuitive in learning the clinical datasets in the identification of attributes and relationships between the health information of patients [40]. The recommended strategy [41] has obtained heart-related data from UCI based repository for classification analysis [42]. It has performed an analysis of the four different kinds of tree-based classification methods for the determination of precision, accuracy and sensitivity of the algorithms. The RF, M5P and reduced error pruning tree mechanisms are the various kinds of tree structures which has performed classification after the feature selection performed on the dataset [43]. Three features-related algorithms have been utilized in the suggested strategy [44] such as recursive features elimination, Lasso-based regularization and Pearson correlation for a better level of prediction [45]. These three feature selection techniques have been applied separately with four tree-based classifications and performance analysis has been computed and evaluated and identified that the combination of Pearson with Lasso has achieved a greater level of accuracy compared to other methods [46].

The better outcomes have shown the effectiveness of the algorithms. ML has provided numerous solutions for reducing and understanding disease symptoms [47]. The considered technique [48] has provided a dimensionality reduction mechanism and has applied a feature selection method in which analysis has been performed from UCI based heart disease repository [49]. It has contained 74 features through which validation has occurred with six various ML-based classifiers. From the inference obtained, it has been found that chi-square combined with principal component analysis (PCA) along with RF has gained satisfied accuracy [50]. The derived features have considered physiological based and anatomical relevance such as chest pain, heart rate, depression in heart vessels and cholesterol level for the detection of cardiac failures [51]. The evaluations have discovered that the integration of PCA with chi-square has provided better outcomes [52]. The utilization of PCA with the raw data from the dataset has obtained lower results and has improved with the higher dimensionality outcomes [53]. In order to imply the technical advantages of quantum-based computing, the development of noisy related intermediate scale-based quantum paradigm has been utilized for speeding up the supervised ML algorithm specifically with the k-means clustering technique [54]. The quantum circuit in the recommended research [55] has performed distance calculation for the process of clustering. The collaborative data mining technique with the quantum-related computation [56]. The extracted input data from the dataset has been pre-processed and classification with the quantum methodology has been applied to the k-means clustering concept [57]. The comparative analysis performed between the classical method of clustering with the quantum idea has revealed the potential of quantum-based learning in terms of accuracy in the identification of heart syndrome [58].

The review made on existing studies has utilized many intelligent prediction methods in artificial intelligence (AI) based classifiers for effective detection of heart disease with health-oriented data collected from the medical dataset. The common limitations concerning the validation of prediction have been analyzed from the existing literature and are listed as follows

- Effective feature selection strategies such as SVM and GWO have predicted the occurrence of heart problems but can be integrated with classifiers to enhance the accuracy of outcomes and also to obtain the robustness of the approach [33].
- The fat quality determines the risk of heart disease. Therefore, the explorations on added dietary attributes and clinical predictor variables can provide further insights into the accurate diagnosis. NN-based learning can solve the imbalanced positive and negative form of classification that occurs in similar medical datasets and thereby improves the prediction accuracy greatly [15].

3. Proposed Methodology

The proposed classification method utilizes quantum-based learning with ML and DL technique for obtaining changes in the health data acquired from the dataset for predicting heart disease in patients at an earlier stage which assists in the faster recovery of patients. The particular patient who has been affected needs to be isolated and classified accordingly to mitigate the progression of the disease and also to follow up on the appropriate clinical treatment. The proposed methodology mainly focuses on reducing the rate of mortality through an earlier detection approach. However, existing studies have suffered with the prediction accuracy, the proposed model is being designed on enhancing the level of accuracy with the utilization of instance-based quantum ML and DL techniques. The architecture diagram of the model is illustrated in Figure 1.

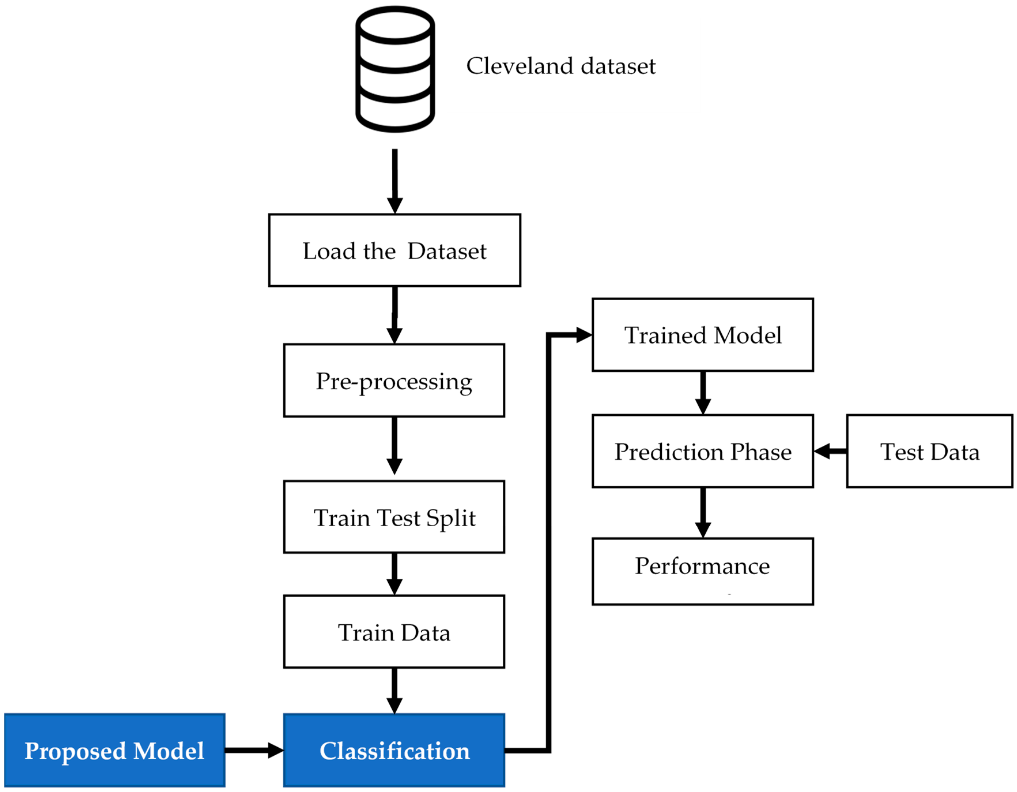

Figure 1. The overall architecture of the proposed system.

The entire working process of the proposed prediction system is given in Figure 1 in which the process is segregated into pre-processing and classification. The input dataset taken for the proposed analysis is the Cleveland heart disease dataset. The input data in the database are taken from the patient's health-oriented test results with different predictor attributes. The collected data are then pre-processed with the checking of missing values and complexities in the structure of data are minimized by the dimensionality reduction. Followed by that, the process of training and test split of input data is being performed accompanied by classification which is being implemented with two stages. The first stage performs the prediction of disease with three kinds of individual classifiers such as DT, RF and SVM separately and the outcome is computed accordingly. The second stage of computation is being performed with the proposed instance-based quantum ML and DL technique for analyzing the input data. It effectively identifies the patterns based on the correlation between features. The proposed quantum model gains accuracy and enhances the classification efficiency compared to other classification methodologies.

3.1. Classification with SVM

SVM is considered to be the significant learning algorithm utilized for classification purposes in ML. It has the potential of creating an effective decision-based boundary that segregates dimensional space into different classes which can classify the newly entered data into the appropriate category. The best boundary is referred to as the hyper-plane. It figures out the extreme level of points or vectors which assist in creating a hyper-plane. Such extreme vectors are called support vectors. Whether the patient is affected with heart disease or not is determined by two categories which are classified with the hyper-plane in the algorithm. The step-by-step operation of SVM is given in Algorithm 1.

Algorithm 1: Support Vector Machine

Input :
  N_{inp_v} (number of input vectors),
  N_{sv} (number of support vectors),
  N_{f_sv} (number of features in support vector),
  $SV[N_{sva}]$ (denoted as support vector array)
  $IN[N_{ina}]$ (as input vector array),
  bi^*(bias)
Output :
  1D1, D2(Decision function outputs)
  for i $\leftarrow$ 1 to N_{inp_v} by 2 **do**
  $1D1 = 0, D2 = 0$
  for j $\leftarrow$ 1 to N_{sv} by 1 **do**
  $dist1 = 0,\ dist2 = 0$
  for k $\leftarrow$ 1 to N_{f_sv} by 1 **do**
  $dist1+ = (SV[j].feature[k] - IN[i].feature[k])^2$
  $dist2+ = (SV[j].feature[k] - IN[i+1].feature[k])^2$
  end
  $k1 = \exp(-\gamma\ \times dist1)$
  $k2 = \exp(-\gamma\ \times dist2)$
  $D1+ = SV[j\}.a^* \times k1$
  $D2+ = SV[j\}.a^* \times k2$
  end
  $D1 = D1 + b^*$
  $D2 = D2 + b^*$
end

From Algorithm 1, it is clear that every element of the support vector is being accessed sequentially and utilized for the computation with the appropriate element of the input vector. The variable N_{inp_v} is denoted as the input vectors, N_{sv} as the support vectors, N_{f_sv} represents the features and $SV[N_{sva}]$ as the array of support vectors. The attribute bi is depicted as bias. The number of features taken for analysis is represented as a feature [k] with D1 and D2 being the outputs of decision functions. When the first feature is received, the hierarchical on-chip-based cache searches for the data. If the cache does not hold the data, the request for the information is sent to the main memory since it possesses a group of support vectors. The requested information is being encompassed as a block to the cache. That specific block is grouped in the cache and the required element is taken from the register. When the second feature is obtained from the next level of iteration with a k-loop, the cache block is capable of holding multiple different vectors and every block is read from memory for accessing all elements of the support vector. Thus the input vectors are computed simultaneously and optimally to classify the disease-affected patients. The performance of SVM is tested with metrics such as accuracy, precision, recall and F1-score for determining the efficacy of the classification structure.

3.2. DT (Decision Tree) Classification Algorithm

DT is increasingly utilized for the classification of disease problems and performs the task of deploying mathematical formulations for predicting the variable and its corresponding thresholds for the splitting up of input data into various subgroups. It is repeatedly performed at every leaf node until the entire tree is constructed. It is easier due to its hierarchical nature. It is also capable of modelling complex functions. DT classifiers are built with two phases as growth and pruning phase. The first stage of the algorithm is being developed with the construction of recursive splitting up of training dataset based on effective criterion until data belongs to every partition having a similar class-label [59]. The generic functioning of the DT is given in Algorithm 2.

Algorithm 2: Decision Tree

GenDecTree(sample S, Features F)
 Step 1. Ifstopping _condition(S, F) = true then
 a. Leaf = createNode()
 b. leafLabel = classify$(s \epsilon S)$
 c.return leaf
 Step 2. root = createNode()
 Step 3. root.tes _condition=findBestSpilt(S,F)
 Step 4. $\mathrm{V} = \{\mathrm{v}\ |\mathrm{v}$ a possible outcome $\sim \mathrm{test}_{\mathrm{condition}}\}$
 Step 5.For every value $\mathrm{v} \epsilon \mathrm{V}$:
  a. $\mathrm{S_v} = \{\mathrm{s} \mid \mathrm{root.test\_condition(s)} = \mathrm{v}$ and $\mathrm{s} \epsilon \mathrm{S}\}$;
  b. Child = TreeGrowth $(\mathrm{S_v}, \mathrm{F})$;
  c. Add child as descent of root and label the edge $\{\mathrm{root} \rightarrow \mathrm{child}\}$ as v
 Step 6. return root

DT working operation as indicated in Algorithm 2 illustrates that it follows a hierarchical tree-based structure consisting of a root node with the function of createNode(), internal node, branches and leaf nodes with leafLabels performing the classification using classify(s). The variable S is denoted as samples and F is represented as features. The pruning stage minimizes the over-fitting by reducing the simultaneous branches in order to sufficiently build the tree for generalizing the framework. The process of pruning is involved with the bottom-up or vice versa traversal of DT while eliminating the outliers and noisy nodes which enhances significant criteria in the tree. It effectively prunes by mitigating errors, descriptive message lengths and critical values. The classification accuracy is efficiently enhanced in the pruning process. The DT classifier iteratively computes and predicts the outcome finally at the root node. The efficiency of DT is being validated through performance metrics for examining the classification model.

3.3. Random Forest

RF is a supervised MLbased classification model consisting of numerous decision trees. It utilizes the bagging and random feature adoption while constructing every individual tree which tries in creating an uncorrelated group of trees as a forest in which prediction by the group is more accurate than individual trees. It performs the information gain and entropy-based classification for selecting the significant feature and utilizes it for branching. It limits the complication of over-fitting. The working operation of RF is illustrated in Algorithm 3.

Algorithm 3: Random Forest

1 : Select randomly Rfeatures from the feature set.
2. For each x in R
  a. calculate the information Gain
  $\mathrm{Gain}(t,x) = G(t) - G(t,x)$
  $G(t) = \sum_{i=1}^{c} -p_i \log_2 P_i$
  $G(t,x) = \sum_{c \in X} P(c)G(c)$
  Where $E(t)$is the entropy of the two classes , $G(t,x)$ is the entropy of features x.
  b. select the node d which has the highest information gain
  c. split the node into sub $-$ nodes
  d. repeat steps a, b and c to construct the tree until reach minimum number of samples required to split
3. Repeat steps 1 and 2 for K times to build forest of K trees

From Algorithm 3, it is clear that RF executes in two phases in which the first phase randomly generates the forest by the combination of N number of decision trees and the second phase is to create predictions for every tree generated in the initial phase. Initially, the algorithm randomly selects the R number of data features from the dataset. Based on the selected features, the DT is being built and chooses the N number of trees. Steps 1 and 2 are repeated k number of times to build the tree k number of trees. The information gain is being formulated using the function Gain (t, x) where E (t) is considered to be the entropy of different classes. When a new data feature enters, the algorithm performs prediction for every DT and assigns the new data points to the appropriate category that wins out the majority votes. The dataset is segregated into subsets and provided to every DT created. During the training process, every DT produces a prediction outcome and when new input arrives, based on the majority of results, RF predicts the final result. K number of trees are utilized for predicting the class label and then majority voting is performed for deciding on the final label. Thus, the RF classifier performs classification and performance is evaluated with metrics.

3.4. Proposed Instance-Based Quantum ML and DL Approach

The conventional ML and DL techniques through subsets of supervised and unsupervised learning have assisted in the identification and classification of patterns from a wide range of data. However, there occurs the need for managing, organizing and classifying diverse data effectively with higher accuracy in numerous organizations and different fields. In order to eradicate the limitations, an instance-based quantum learning approach is used in the proposed work for effective prediction outcomes based on learning techniques in different input data. It is considered to be versatile and the adaptive learning technique of the proposed method autonomously predicts the possible group of patterns and behaviours for solving complex problems. Even though conventional algorithms have been observed to be efficient in mapping patterns, still certain complexities exist which affect the accuracy of the model. It is being solved through quantum learning in which the input data is shown for preparing the model where both unitary and complexity system is being developed. After the development, feature extraction is accomplished. Followed by that instance-based quantum ML algorithms are applied for predicting the outcome. The architecture model of the proposed framework is depicted in Figure 2.

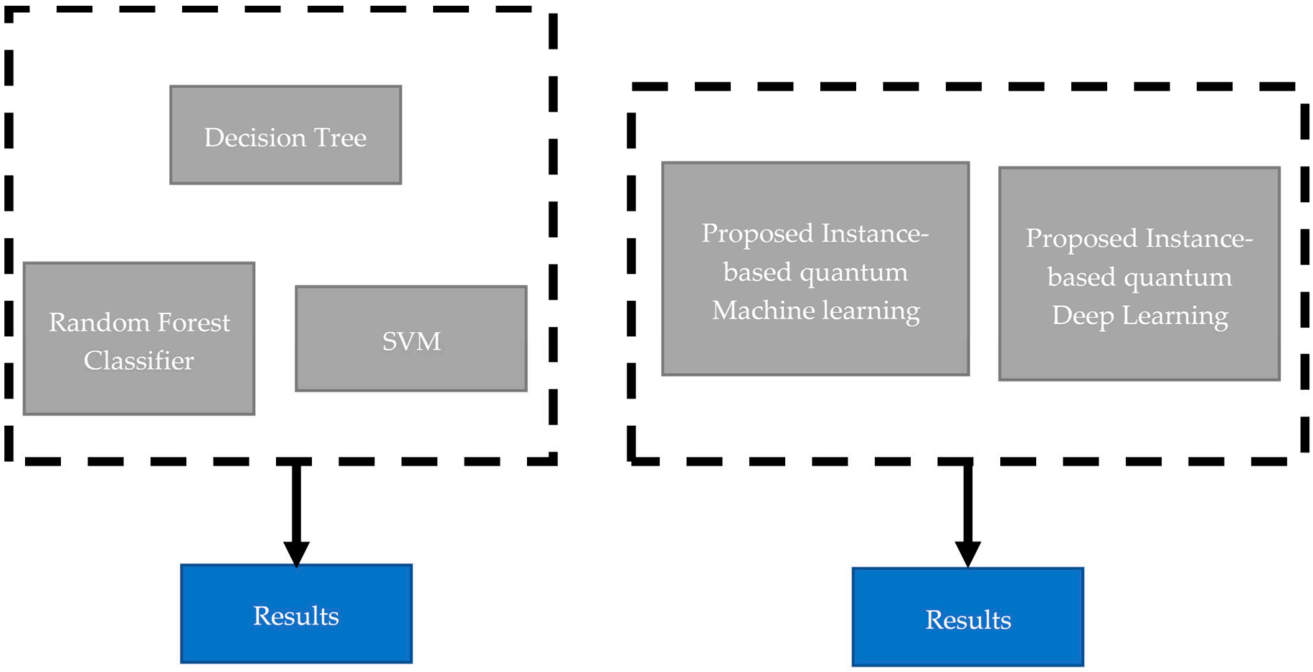

Figure 2. Architectural framework of the proposed classification algorithm.

The classification process in the proposed research is being implemented with two phases as given in Figure 2. The first phase involves three kinds of classifiers such as DT, SVM and RF. The three models are evaluated individually for validating the efficiency of each classifier. The other phase is the proposed classification technique performed with instance-based quantum ML and DL approach and it is also validated for determining the efficiency of the proposed model. Quantum computation manipulates information using quantum theory and is considered to be the group of assertions which can be executed on systems. The quantum algorithms designed with NN and graphical frameworks relied on Grover search which increases the speed of unordered datasets. It effectively reduces the training time and handles the topology of the complex network. It also automatically fine-tunes the hyper-parameters and performs the complex tensor and matrix formulation at a higher speed and used quantum-based tunnelling to achieve the functional objective. The proposed model in the health care field concentrates on predicting heart disease from patient data which is being formulated with quantum physics that enables the computers for processing the data more quickly. Moreover, qubits (quantum bits) are being included with quantum computing in which data units exist in an ON state or OFF state with quantum superposition which allows the particles to exist in various states and provides enormous flexibility and power for solving complex issues. It also provides the quantum gate which acts as the group of quantum states referred to as basis states that produce the desired outcome. ML and DL algorithms are used with computing resources for interpreting and analysing the input data. The interpretation of medical information assists in training the algorithm with quantum manipulation for detecting abnormal discoveries with higher precision. The proposed work provides earlier, highly accurate and fine granular forecasting in which the quantum-based classification aids in the detection of patterns and discovery of abnormal health data and benefits in the prevention of disease progression and for further clinical treatment.

3.4.1. Proposed QML (Quantum Machine Learning) Architecture

The main intention of the proposed work is to investigate the potential of quantum ML for the prediction of heart diseases. It is being dealt with in the Cleveland dataset which uses the bits of 0′s and 1′s as the fundamental element of circuits. It employs the qubit which simultaneously occupies two different states such as 0 and 1 at a similar time.

The superposition of different states allows the operation to run in both a parallel and sequential manner which reduces the number of functions in the algorithm. Moreover, quantum computers allow the particles in gaining a robust correlation with the connection of properties with other significant particles. Inspire by larger distances, qubits are correlated which speeds up the task of prediction. The architecture diagram of quantum-based ML is given in Figure 3.

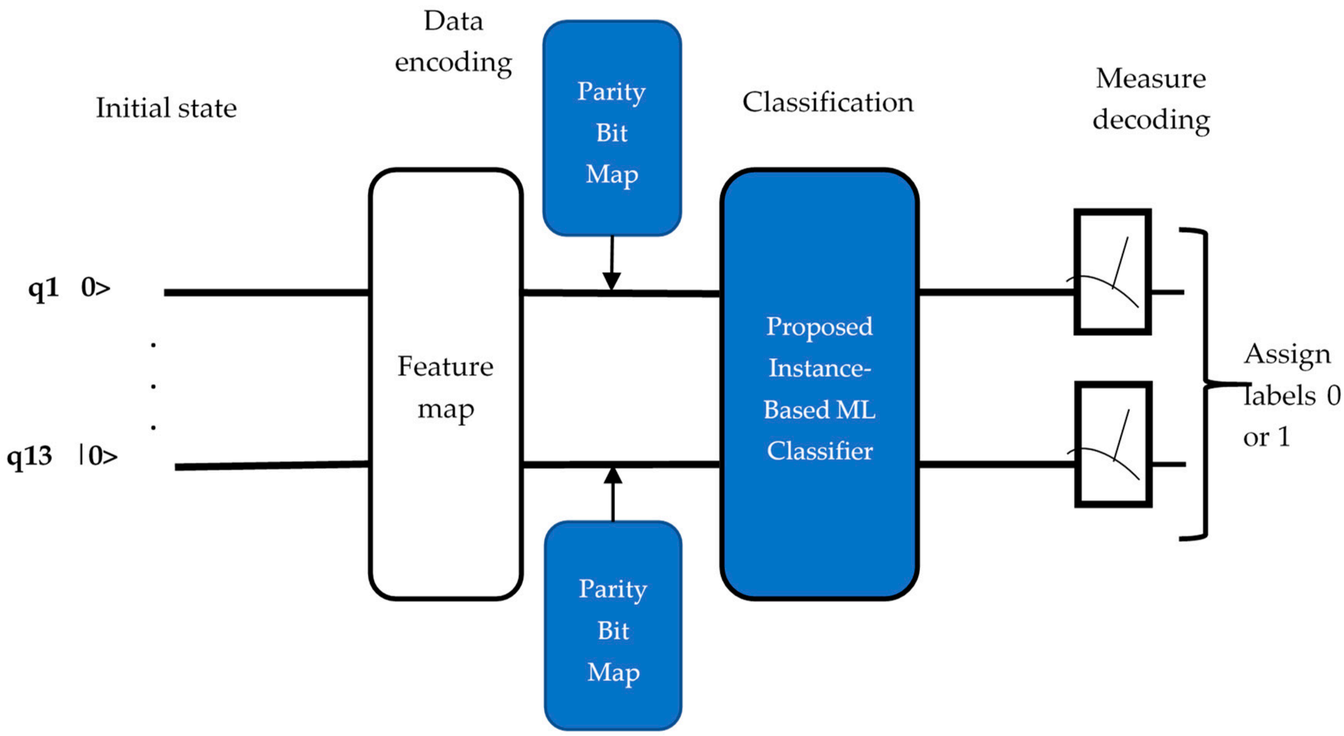

Figure 3. Block Diagram of Quantum-based ML algorithm.

The instance-based quantum classifier is illustrated in Figure 3, in which supervised learning employs circuits for performing the task of classification. In this approach, the data is mapped into the quantum state with the utilization of a feature map circuit along with the implication of parameterized circuit to the feature state. The feature vectors are being mapped into the quantum spaces with the utilization of feature maps consisting of two qubits. After the process of fitting the classifier with training data features and performing testing with the framework using test data, binary value measurements perform decoding of quantum data into the classic values of 0 and 1.

3.4.2. Proposed Quantum Deep Learning (QDL) Architecture

Quantum NN follows the method of feedforward networks in which the model takes the input data from a single layer of qubits and passes it on to the other qubit layers which evaluate the data and passes on to the output of the next layer which eventually leads the path to the final layer. It does not hold an equal number of qubits before and after. The structure is being trained in the path of ANN with quantum computation with classical input data. The proposed QDL is depicted in the following Figure 4, wherein q denotes qubits and R denotes functional gates.

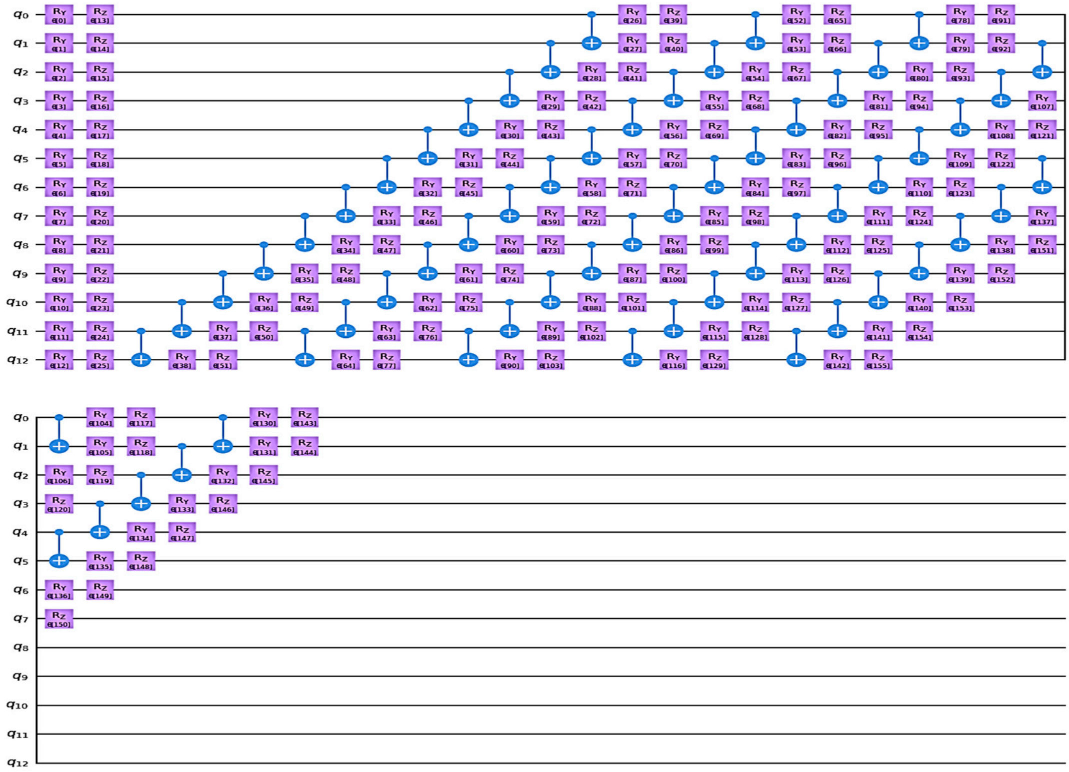

Figure 4. QDL Functional Diagram.

The operation of QDL is illustrated in Figure 4 which indicates that after the process of encoding input data features into a specific quantum state, instance based parameterized quantum-oriented circuit is applied in order to execute a sequence of linear transformations. Generally, n-qubit is represented as

$$\mathrm{UG_{PQC}}\left(\vec{\theta}\right)|\varphi_{\mathrm{in}}\rangle = (\textstyle\prod_{i=0}^{m-1} \mathrm{UG_i}(\theta_i)|\varphi_{\mathrm{in}}\rangle, \tag{1}$$

In which $\mathrm{UG_{PQC}}\left(\vec{\theta}\right)$ holds the unitary-gates and $\mathrm{UG_i}(\theta_i)$ consists of parameters where m is the representation of the number of quantum gates, PQC denotes the parameterized quantum circuit, φ_{in} denotes the input state. During the process of learning, parameters are optimized with the conventional adam-optimizer since the initial form of states evolves to the desired state through the operation of the circuit. Two kinds of unitary gates are considered in such a way of parameterized based quantum-gates as

$$\mathrm{UG_i}\left(\vec{\theta_i}\right) = \exp\left(-i\theta_i Z_j Z_k\right) \tag{2}$$

In which it acts on qubits j and k. Since it is not recommended as the universal gate, every element is being decomposed into the constant form of an elementary level gate-set. From Equation (2), every $\mathrm{UG_i}\left(\vec{\theta_i}\right)$ is being decomposed into two different CNOT gates and a single rotational form of Z level gate with the angle representation of $2\theta_i$. The instance circuit is considered to be a significant part of the quantum circuit for performing the manipulation. The QDL holds the potential of disentangling the input state even with the limited amount of quantum gates. The group of quantum gates with various parameters is being computed on every pair of nearest-neighbour range of qubits which allows the process of capturing the quantum correlations on a particular scale of a similar layer on the network. In the input level of the state, the data is embedded into the quantum-based subsystem. The quantum-based computation extracts the hidden information efficiently. The important purpose of utilizing the unitary gate is to eradicate the superposition in the quantum-oriented data by leaving the data containing label. Post-level processing is implied for extracting significant information. The quantum-based NN includes the operation of the normal workflow of tasks in quantum information preparation, the embedding of data, training the network, optimization of parameters and achieving probability as the outcome. For the calculation of the entanglement with the quantum-oriented NN, the focus lies on detecting and quantifying the measure of whether the state of the quantum is continuous or discrete. A discrete QNN is considered to be the quantum of circuits with quantum designed perceptron which is arranged into several hidden layers with different unitary operations and acts upon the input level of quantum conditions and yields an appropriate output in the form of quantum states. The individual qubit register is utilized in the network for parameterized quantum circuits with input and output and represents quantum-based neurons as the map. Based on the implementation of artificial neuron implementation in quantum-oriented circuits, the computation in quantum needs training through efficient back-propagation resembling method. The output of the network is represented as the configuration of a series of layer-by-layer transition maps.

$$\rho^{\text{out}} = \vartheta^{\text{out}}\left(\vartheta^{L}\left(\ldots\vartheta^{2}\left(\vartheta^{1}\left(\rho^{\text{in}}\right)\right)\ldots\right)\right) \tag{3}$$

where $\vartheta^{l}(\rho) = \text{tr}_{l-1}(\prod_{j=ml}^{1} U_j^l(\rho \otimes |0\ldots.0>_l< 0\ldots0|)\prod_{j=ml}^{1} U_j^l)$

$$UG_{PQ}\left(\vec{\theta}\right)|\varphi_{in}\rangle = (\prod_{i=0}^{m-1} UG_i(\theta_i)|\varphi_{in}\rangle, \tag{4}$$

In which U_j^l is considered to be the number of quantum neurons operating on layers and $UG_{PQ}\left(\vec{\theta}\right) \mid \varphi_{in}$ represents the proposed parity bit for instance-quantum circuits. The continuous type of quantum variable system is used for defining perceptron in which the architecture of QDL is being optimized in the construction of Tensor-Flow of the backend with strawberry fields through the quantum photonic organization for providing quantum-oriented solutions. Generally, the QNN with a continuous variable is being built with numerous layers contained with the series of gates such as,

$$\mathcal{L} := \phi \circ D \circ U_2 \circ S \circ U_1 \circ UG_i\left(\vec{\theta}_i\right) \tag{5}$$

where equation 4 represents the both single and double mode of combinational-rotational gate denoted as U_1 and U_2 along with $UG_i\left(\vec{\theta}_i\right)$ parameterized gates and S as the squeezing form of the transformational gate and D as the displacement gate. The variable ϕ signifies the non-Gaussian gate from the right to the left side of the equation respectively in defining the Gaussian system as $D \circ U_2 \circ S \circ U_1$ which illustrates the bias and weight transformation from traditional NN to quantum NN. The quantum circuits that measure the quantum state are capable of returning numbers randomly at the same time. The interference of quantum in preparing states and loading regular data into states solves the complexities of state-level collapse. Hence, it is being found to be flexible in inputting, measuring and simulating QNN. The final layer of QNN output is achieved through measurements of final states and sent to computers. The discrete form of variable in QNN utilizes positive operator valued measurement (POVM) and homodyne detection operator (HDO) is used for the continuous variable QNN.

4. Results and Discussion

The performance of the proposed model is evaluated with the rate of prediction computed with the classification algorithms. The following section describes the computation result with the internal comparison and comparative analysis being performed with other algorithms to predict the effectiveness of the proposed structure with respect to evaluation metrics such as accuracy, precision, recall and F1-score.

4.1. Dataset Description

The Cleveland heart disease is the dataset from the UCI repository utilized in the proposed model which is considered to be the collection of health-related patients records with multivariate characteristics and its primary intention is to predict the presence and absence of disease through changes in heart functional attributes in the form of csv files. The Cleveland dataset consists of 76 attributes in all 303 cases. The dataset contains information on the patients such as their age, patient identification number, and location, variety of health data, type of chest pain, ECG readings, and measurement of blood pressure, fasting blood sugar and cholesterol level. Though the Cleveland dataset [60] has 76 attributes, only 14 attributes are used by most of the researchers. The dataset is available at https://archive.ics.uci.edu/ml/datasets/heart+disease (accessed on 2 January 2023).

4.2. Experimental Results

The dataset utilized for the proposed work is Cleveland heart disease data and the computational result obtained from each algorithm is illustrated in this section. The simulation outcomes in terms of a correlation matrix, confusion matrix and receiver operating curve (ROC) which is measured for the classification problems at different threshold values exhibit the capability of the model in the process of distinguishing between the classes. The proposed prediction mechanism is being analyzed through the correlation matrix depicted in Figure 5.

Figure 5. Correlation matrix representation.

The correlation coefficients within the variables are depicted in Figure 5. The darker portions determine the higher level of correlation in confirming the cardiac disease and the lighter portions signify a lower correlation which depicts the absence of disease occurrence in patients. The rate of prediction and classification is illustrated in the following Figure 6.

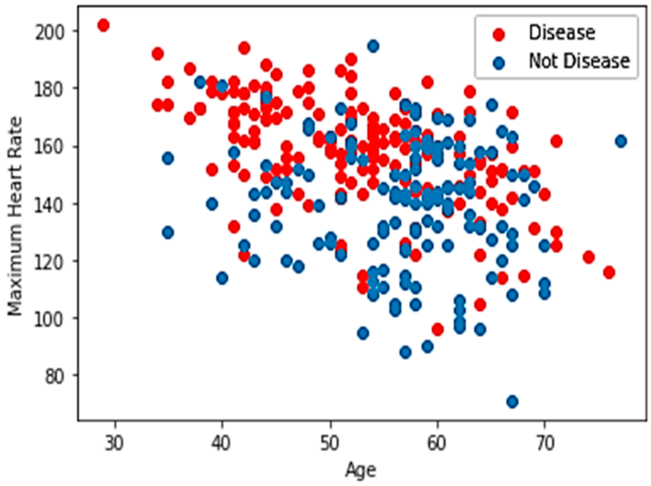

Figure 6. Classification of patients with heart disease.

Based on the level of heart rate as mentioned in Figure 6, the proposed quantum learning efficiently classifies the patients in the dataset with heart disease and non-affected cases accurately at all age groups. It exhibits the significance of the proposed model in the medical field for the prediction of cardiac irregularities. The classification performed with three different algorithms is evaluated individually and then compared with the proposed model for determining the accuracy efficiency of the proposed quantum system.

4.2.1. Support Vector Classifier

The experimentation with the SVM classification algorithm for the prediction of disease related to the heart is being evaluated with a confusion matrix and ROC graph as follows.

The combination of actual and predicted values is illustrated in Figure 7. From the positive and negative classes, the number of actual predictions was found to be high which shows the better accuracy of the system. The ROC for the SVC is given in Figure 8.

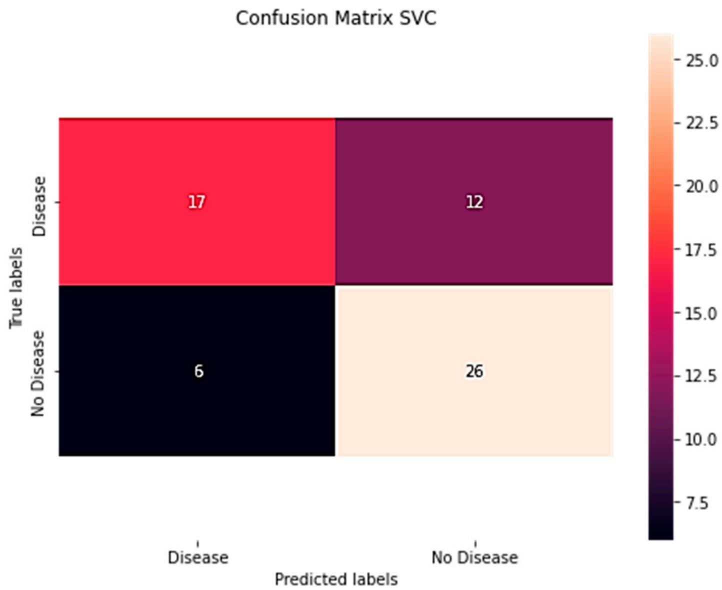

Figure 7. Confusion matrix for SVC.

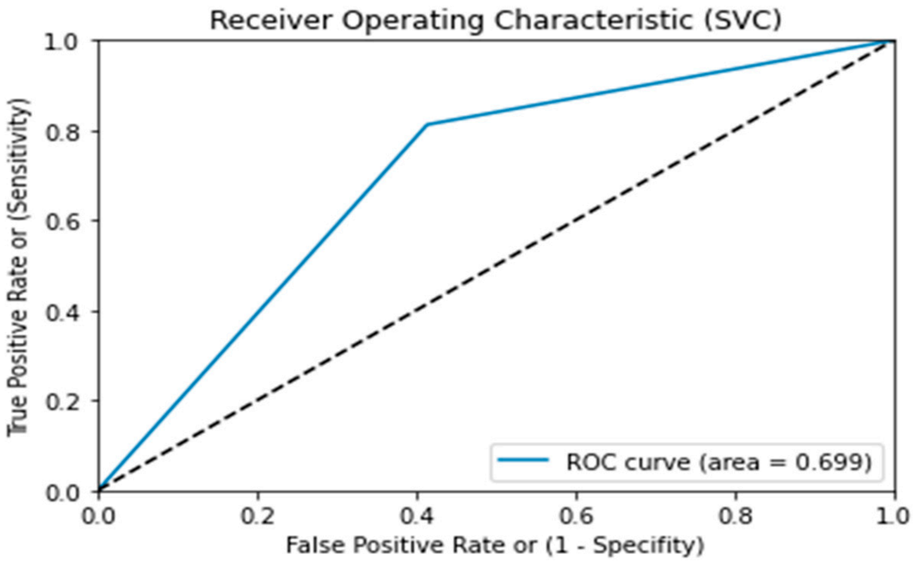

Figure 8. ROC graph for SVC.

The ROC value obtained with the SVC technique given in Figure 8 illustrated that an area value of 0.699 acquired from the classification framework provides that the system is efficient and it has the ability for diagnosing patients with and without heart disease based on the classification evaluation.

4.2.2. Decision Tree

The ROC and confusion matrix measurement for the prediction of cardiac failure with the utilization of DT classifiers is evaluated for estimating the efficiency of the system. The confusion matrix for DT is given in Figure 9.

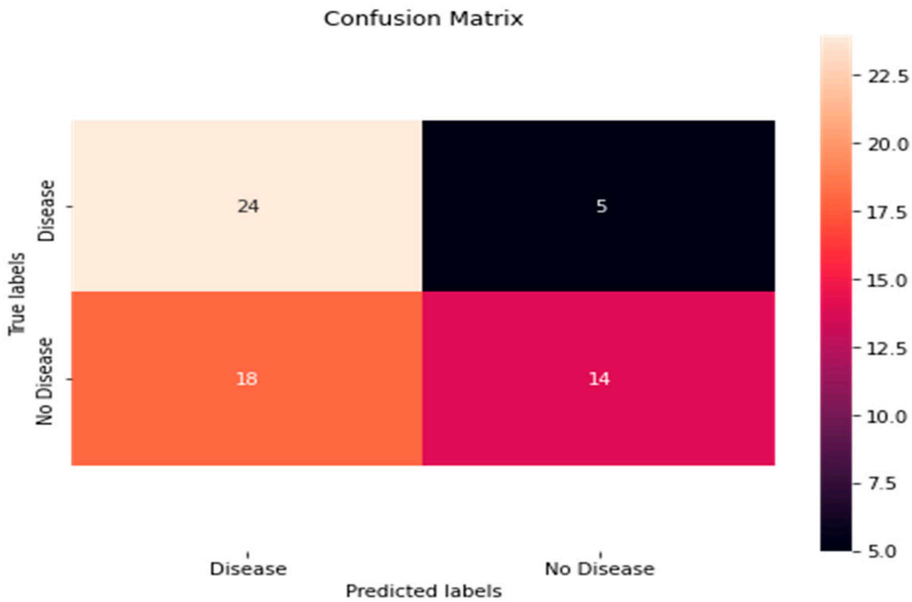

Figure 9. DT evaluation with the confusion matrix.

Figure 9, clearly indicates the predicted and actual values obtained from the classifier in which the analysis from true and false values, the actual prediction values are higher exhibiting the effectiveness of the classifier. The ROC graph for DT is illustrated in Figure 10.

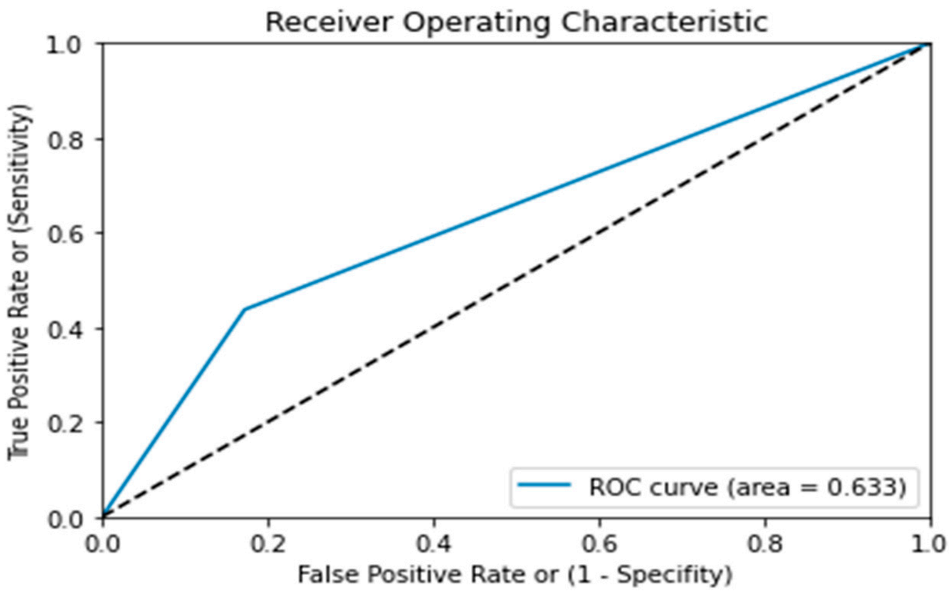

Figure 10. ROC estimation for DT Classifier.

The graph analysis in Figure 10 for ROC with DT obtains a value of 0.633 from the classification analysis which exhibits the potential of the classifier in differentiating the affected and non-affected patients through the computation of the algorithm.

4.2.3. Random Forest

The performance of the RF classifier is calculated using the confusion matrix and ROC from the obtained classification outcome for detecting the significance of the model. The representation of the confusion matrix with RF values is given in Figure 11.

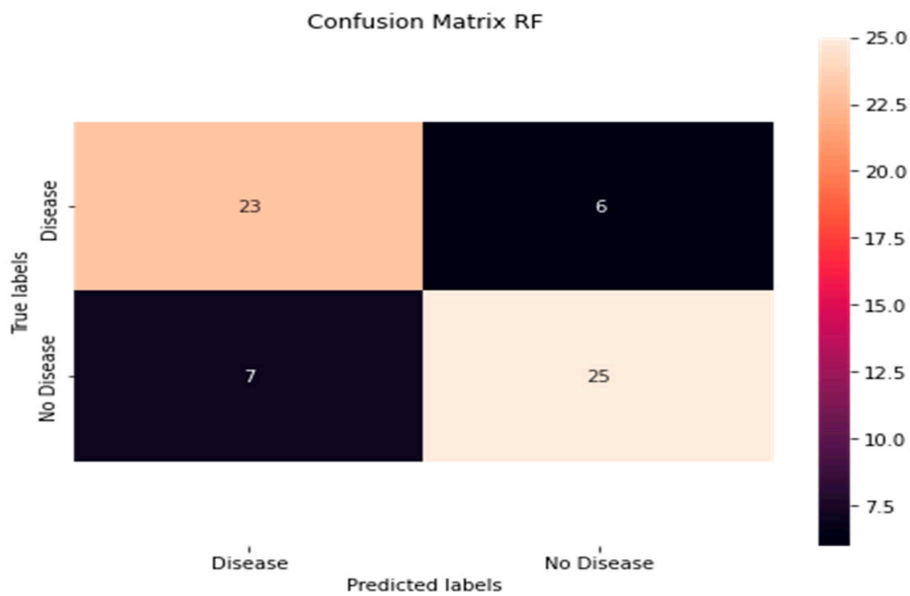

Figure 11. RF assessment with the confusion matrix.

From Figure 11, the actual results along with predicted value estimation are manipulated which determines the satisfied accuracy level of the system ad ROC for RF is provided in Figure 12.

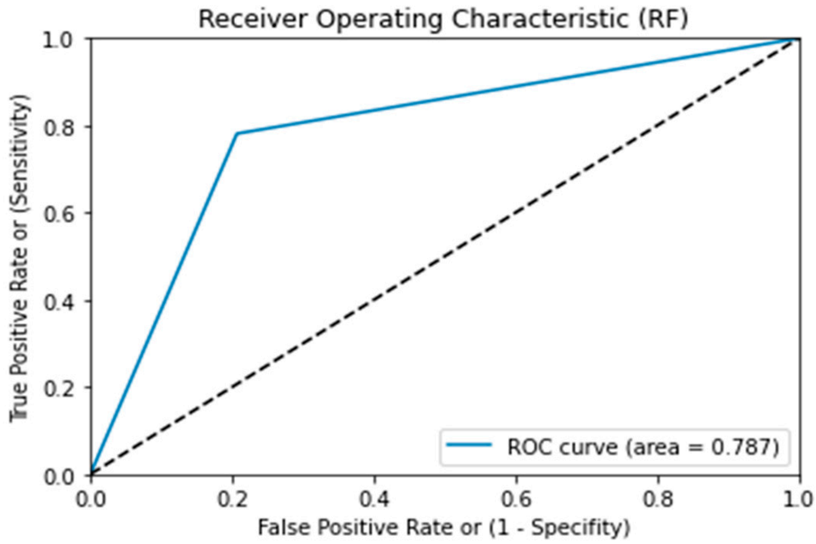

Figure 12. ROC analysis for RF.

The estimation of ROC obtained with the RF technique given in Figure 12 indicates that an area value of 0.787 obtained from the classification provides that the model has efficiency in classifying the patients affected with heart disease.

4.2.4. Proposed Quantum Learning Evaluation

The estimated results obtained from the three kinds of classifiers have shown classification accuracy. However, the implication of the quantum-based learning technique exhibits a higher level of accuracy which is being analysed through ROC and confusion matrix.

The matrix values of predicted and actual observations depicted in Figure 13 show that in the analysis made from true positive and true negative classes, the actual detected values are significantly high compared to the three classifiers. The ROC graph for the quantum learning process is given in Figure 14.

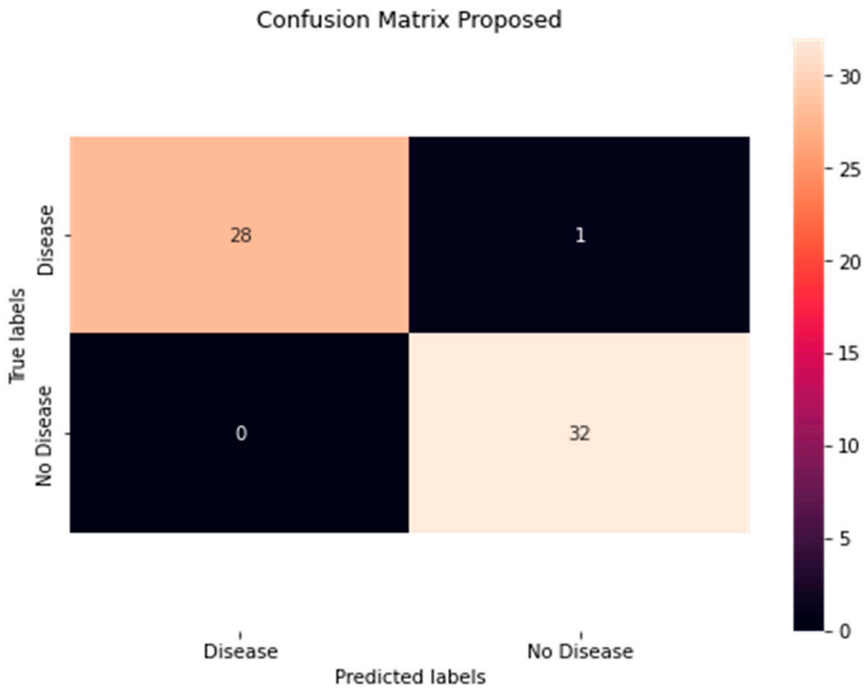

Figure 13. Proposed confusion matrix representation.

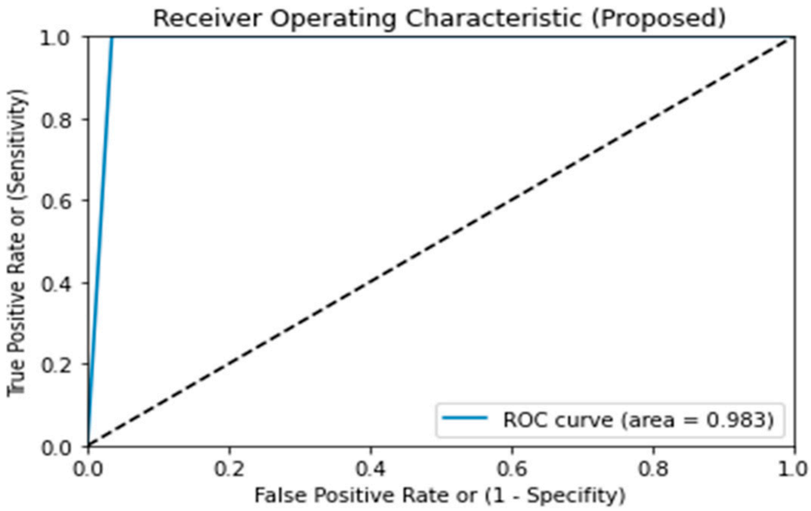

Figure 14. ROC analysis for proposed quantum approach.

The graph observation in Figure 14 shows that the area value of 0.983 acquired from the proposed classification that the quantum model is efficient through a greater level of accuracy obtained in accurate diagnosis and distinguishing heart disease-affected patients from the dataset.

4.3. Performance Analysis

The efficiency of the proposed work is estimated for the evaluation of the system with different performance metrics such as accuracy, precision, recall, specificity, sensitivity and F1 score. The following section describes the analysis made with the experimentation of the system and the comparative analysis being performed. The systematical assessments and evaluations obtained from the existing and proposed classification presented in the next section.

4.3.1. Internal Evaluation

The internal assessment of the classification algorithms and proposed quantum learning algorithms are performed for identifying the efficiency of the proposed work. RF-based validation is given in Table 1.

Table 1. Evaluation with RF Classifier.

Metrics	Random Forest
Accuracy	0.79
Precision	0.79
Recall	0.79
F1-Score	0.79

From Table 1, it is evident that the RF classification achieved a 0.79 value of accuracy, with a precision of 0.79. The recall and F1-score were also observed to be 0.79. The values obtained through SVC are given in Table 2.

Table 2. SVC-based Performance Evaluation.

Metrics	SVC
Accuracy	0.70
Precision	0.71
Recall	0.70
F1-Score	0.70

The process of classification performed with the SV classifier is being evaluated and the obtained values are given in Table 2 and reveal that it achieved an accuracy value of 0.70, a precision of 0.71, recall values and F1-score values acquired are 0.70 respectively. The DT classification analysis is given in Table 3.

Table 3. Assessment with DT classification.

Metrics	Decision Tree
Accuracy	0.62
Precision	0.65
Recall	0.63
F1-Score	0.61

The observations obtained from Table 3 indicate that the DT classifier has attained an accuracy value of 0.62, a precision of 0.65, recall values recorded as 0.63 and the F1-score is found to be 0.61. The performance evaluation of the algorithms has shown their ability in the prediction of heart diseases. The following evaluation depicts the performance of the proposed quantum learning model. The QML validation is provided in Table 4.

Table 4. Performance evaluation of proposed quantum-based machine learning.

Metrics	Instance-Based Quantum Machine Learning
Accuracy	0.836065574
Precision	0.8385
Recall	0.8274
F1-Score	0.8374

From Table 4, it is clear that the proposed system is highly efficient through an observed accuracy value of 0.836, precision of 0.838, recall values of 0.82 and F1-score value of 0.8374. It illustrates the efficiency of the proposed framework in predicting the disease accurately. The graphical analysis of the quantum ML strategy is given in Figure 15.

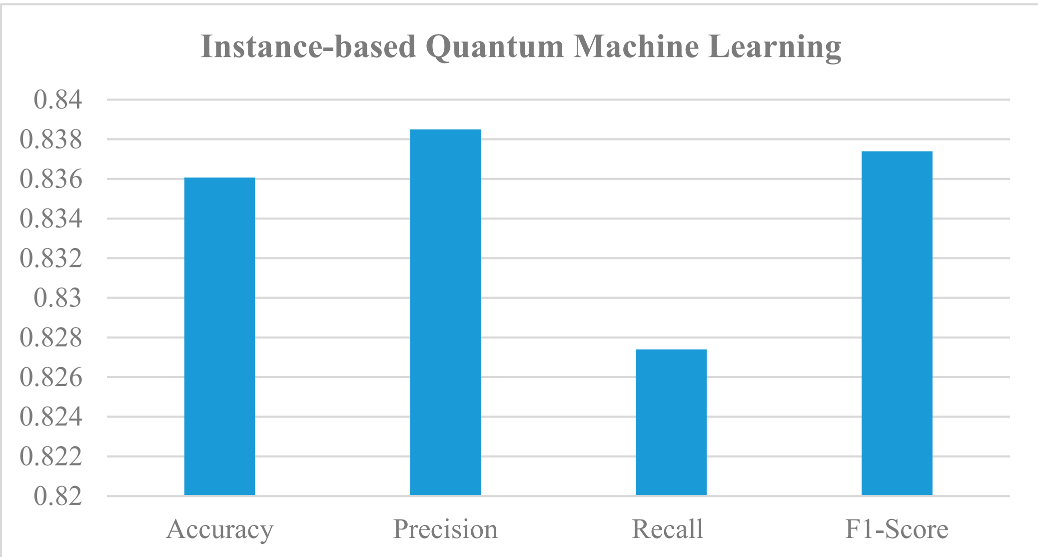

Figure 15. Graphical performance analysis of proposed QML.

The graphical analysis depicted in Figure 15 explains that the proposed work attains a greater level of evaluation metrics which determines the efficiency of the quantum model. The metrics achieved with the QDL representation during the process of classification are given in Table 5.

Table 5. Proposed QDL performance evaluation.

Metrics	Instance-Based Quantum Deep Learning
Accuracy	0.98
Precision	0.98
Recall	0.98
F1-Score	0.98

The proposed QDL-based classification is evaluated, and values obtained in Table 5 show that the proposed QDL achieved a 0.98 value for accuracy, recall, precision and F1-score value. The observed values indicate that the proposed quantum computation in classification is found to be efficient. The graphical view of QDL is depicted in Figure 16.

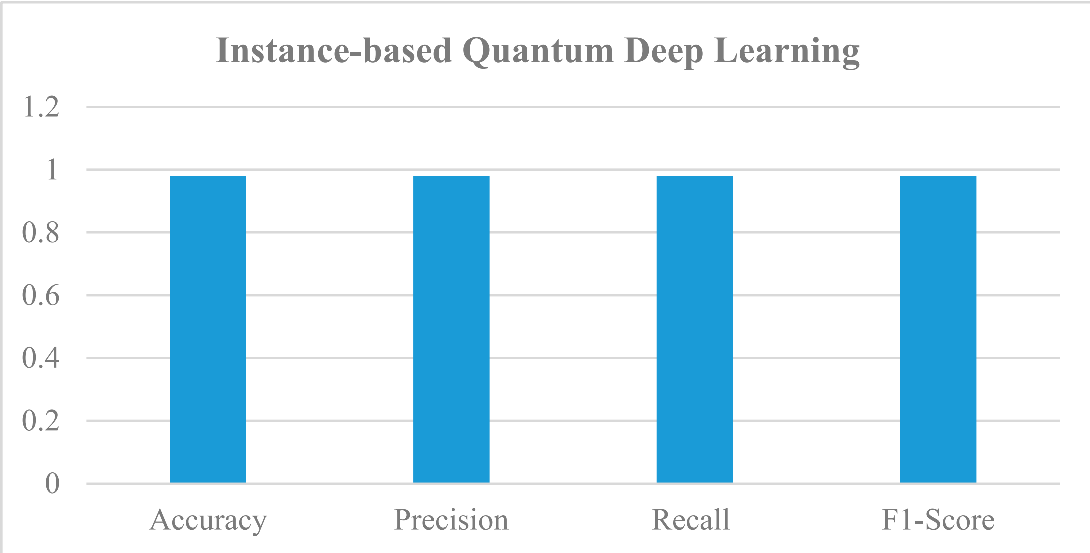

Figure 16. Graphical Representation of the Proposed QDL.

From Figure 16, it is evident that the proposed work is found to be efficient in the accurate prediction of heart diseases and the proposed QNN-based accuracy with qubit representation is given in Table 6.

Table 6. QNN based on Qubit analysis with accuracy.

Proposed Instance Neural Network Accuracy									
	Umber of Qubits = 3			Umber of Qubits = 4			Umber of Qubits = 5		
Number of layers	3	4	5	3	4	5	3	4	5
Accuracy	94.52	95.63	95.87	96.02	96.83	97.31	97.69	98.21	98.36

The recorded values illustrated in Table 6 provide the qubit computation representation of the proposed work achieves a higher level of accuracy with an increase in the qubit values. The internal comparative analysis indicates that the proposed system is efficient in terms of accurate detection and classification of heart diseases from the patients in the dataset. Additionally, K-fold validation has been used in the present study to ensure that each observation present in the original dataset has appeared in the training and test set. Accordingly, the results for K-fold validation are shown in Table 7.

Table 7. K-fold Cross Validation.

QML Heart Disease Prediction Dataset				QDL Heart Disease Prediction Dataset			
K = 5	K = 10	K = 15	K = 20	K = 5	K = 10	K = 15	K = 20
0.83606	0.82	0.82	0.8	0.98	0.97	0.97	0.96

From Table 7, when 5, 10, 15, 20-fold are given for quantum ML heart disease prediction and quantum DL heart disease prediction dataset, it is found that the values of the accuracy have been changed considerably.

4.3.2. External Comparison

The efficiency of the quantum learning method is exhibited through comparative analysis made with the existing classification algorithms [44]. The comparison performed with traditional algorithms [44] is tabulated in Table 8.

Table 8. Comparative assessment with the classification techniques [44].

Model	Accuracy	Precision	Recall	F1_score
IBM-Q and D-Wave	0.86	0.74	0.71	0.71
SMO_NB	0.79	0.84	0.8	0.81
SVM	0.83	0.88	0.81	0.85
Decision Tree	0.85	0.88	0.85	0.86
Existing	0.89	0.88	0.93	0.88
Proposed	0.98	0.98	0.98	0.98

The analysis made from the comparative study in Table 8 indicates that the proposed classification process of quantum-based ML and DL strategy achieved greater values of performance metrics compared to the existing classification methodology. The values obtained from the analysis indicate the classification effectiveness of the proposed work. The present study is found to be efficient in terms of classification accuracy and prediction of data with cardiac disease concerning all metrics such as f1 score, recall, and accuracy and precision. Moreover, the classification procedure involved in the traditional approach [61] is also compared to the proposed model and the observed values are tabulated in the given Table 9.

Table 9. Comparison of the Proposed Model with the Existing Algorithm [61].

Model	Accuracy	Precision	f1_Score
FODW	92%	89%	87%
Proposed	98%	98%	98%

From Table 9, it is clear that the classification efficiency attained from the existing algorithm is being recorded an accuracy value of 92%, precision at 89% and f1-scores of 87% for the existing work. The proposed quantum model achieves 98% of all the considered metrics and from the comparative analysis, it is evident that the proposed classification system is efficient in all aspects and hence holds the potential of providing better classification results. Additionally, the classification accuracy of the proposed algorithm with the various traditional approaches [62] is compared and tabulated in Table 10.

Table 10. Comparative Evaluation [62].

Model	Accuracy
Majority vote model	85.48
PSO	85.71
ANN	87.37
Hoeffding Tree	86.94
Quantum-enhanced ml algorithms	89
Existing	90.16
Proposed	98

From Table 10, it is clear that the proposed model is efficient in terms of accuracy when compared to existing methodologies of classification. The prediction of input data with affected and not affected categories is classified based on classification accuracy. Both categories are classified with an accuracy level of 98% with the proposed technique which is considered to be greater compared to other existing techniques. In addition, the comparison has been undertaken with conventional approaches [63] with regard to accuracy and the results are shown in Table 11.

Table 11. Analysis with regard to Accuracy [63].

Technique Used	Accuracy
CNN & Decision Tree	82%
SVM	84.12%
Naïve Bayes	86.53%
KSOM (Kohonen Self-Organizing Map)	88.90%
C4.5 MAFIA K-means Cluster	89%
DBN (Deep Belief Network)	90%
RNN (Recurrent Neural Network)	92%
Proposed model	98%

From Table 11, the accuracy value of conventional algorithms such as RNN is 92%, while other algorithms such as SVM have scored 84.12%, and CNN and DT have shown 82%. Conversely, the proposed work has a high accuracy of 98%. In addition, analysis has been performed with existing works [64] in accordance with accuracy. The corresponding results are shown in Table 12.

Table 12. Analysis in accordance with Accuracy [64].

Authors/Technique	Accuracy
Risk factor-based approach	86.7
Rmonto ontology-driven data mining approach	90
ANN-based attribute extraction technique	94.7
Decision Tree-based approach	95.5
Existing approach [64]	97
Proposed approach	98

From Table 12, the accuracy rate of conventional approaches such as the risk factor-based approach has been shown to be 86.7%, while, the existing approach [64] has revealed 97% accuracy. Conversely, the proposed approach is 98%, which is higher than existing works. As the proposed system relies on quantum computing, it possessed an innate ability to perform effective learning that has made it accomplish better outcomes than existing works. The accuracy comparison of the proposed work with the existing methodologies shows that the proposed study is efficient in terms of accuracy. The higher the prediction rate of the system, the greater its utility in detecting heart diseases through changes in heart attributes. The quantum-based classification has achieved higher earlier detection accuracy. The proposed research significantly contributes to the healthcare industry. The advantage of the proposed framework is its classification accuracy and the quality of making effective and faster classification of patients with cardiac diseases that assists the patients in taking further clinical procedures for recovery and reduces the rate of mortality considerably.

5. Conclusions

Heart Disease is one of the dreadful diseases affecting various individuals globally. Hence, early detection has become crucial to assist in minimizing the death rate. This study claims that quantum-based ML and DL would assist in predicting heart failure. The proposed prediction model utilized the classification techniques of SVM, DT and RF for predicting the likelihood of heart disease in patients and also performed classification with the proposed quantum-based ML and DL. All the classifier methodology was evaluated individually and compared internally and along with the other traditional algorithms. Based on the results obtained, the proposed technique with quantum systems for the prediction of diseases gained efficiency in terms of accuracy, precision, recall and F1 score. Among the other conventional algorithms, the proposed instance-based quantum algorithms were considered to be efficient in the prediction of heart diseases as quantum-based ML shows an 83.6% accuracy rate, while quantum-based DL showed a 98% accuracy rate. From the experimental evaluation performed on each algorithm, it was found that the proposed work is efficient in accurate prediction compared to other classification algorithms. The computational time (O log n) assists in the efficient running of the proposed method and is more suitable for complex problems. The properties of the quantum-based ML and DL improved the performance of the system by using significant computational acceleration based on complexity at run-time. The earlier stage detection on patients can reduce the computational overhead in future in order to make effective real-time implementation. In future, it would be optimal to use other quantum-based ML and DL approaches to enhance the performance.

Author Contributions: Conceptualization, S.A., A.A., A.B., M.S., A.G. and S.W.; methodology, S.A., A.A., A.B., M.S., A.G. and S.W.; software, S.A., A.A., A.B., M.S., A.G. and S.W.; validation, S.A., A.A., A.B., M.S., A.G. and S.W.; formal analysis, S.A., A.A., A.B., M.S., A.G. and S.W.; investigation, S.A., A.A., A.B., M.S., A.G. and S.W.; resources, S.A., A.A., A.B., M.S., A.G. and S.W.; data curation, S.A., A.A., A.B., M.S., A.G. and S.W.; writing—original draft preparation, S.A., A.A., A.B., M.S., A.G. and S.W.; writing—review and editing, S.A., A.A., A.B., M.S., A.G. and S.W.; visualization, S.A., A.A., A.B., M.S., A.G. and S.W.; supervision, S.A., A.A., A.B., M.S., A.G. and S.W.; project administration, S.A., A.A. and A.B.; funding acquisition, S.A., A.A., A.B., M.S. and A.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Acknowledgments: The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia for funding this research work through the project number (IF2/PSAU/2022/01/22904).

Conflicts of Interest: The authors declare no conflict of interest.

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