A Novel Heart Disease Prediction System Based on Quantum Neural Network Using Clinical Parameters

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Authors' contributions

This work was carried out in collaboration between all authors. Author RN had designed the study with the help of Author SS. Author RN had written the draft of the manuscript. Authors SS and AKG had managed the analyses of the study. All authors read and approved the final manuscript.

Original Research Article

ABSTRACT

Aims: The diagnosis of Heart disease at earliest possible stage is very crucial to increase the chance of successful treatment and to reduce the mortality rate. The interpretation of cardiovascular disease is time-consuming and requires analysis by an expert physician. Thus there is a need of expert system which may provide quick and accurate prediction of Heart disease at early possible stage, without the help of physician.

Place and Duration of Study: The study was carried out during 2010 to 2013 in the vicinity of Yamuna Nagar, Haryana, India.

Methodology: The data used for this study consists of clinical values (Diabetes Mellitus, Low Density Lipoprotein, Triglycerides and High Density Lipoprotein) and has been collected from various Hospitals of 689 patients, who have symptoms of heart disease. All these cases are analyzed after careful scrutiny with the help of the Physicians. For training and evaluation purpose we have carefully predicted the level of heart disease by taking the help of Cardiologist/ Physician. The data consists of patients' record with doctor's predictions/ diagnosis.

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Results: The obtained result of Heart disease prediction match with the expert physician's opinion with 96.97% accuracy and shows high degrees of sensitivity and specificity.
Conclusion: The proposed Heart Disease Prediction System based on Quantum Neural Network gives the high degrees of accuracy in predicting the risk of cardiovascular diseases, are also the best results based on clinical factors. The result generated by this system has been evaluated and validated on data of patients with the Doctor's diagnosis. This system will help the doctors to plan for a better medication and provide the patient with early diagnosis as it performs reasonably well even without retraining. Such an expert system may also prove useful in combination with other systems to providing diagnostic and predictive medical opinions in a timely manner.

1. INTRODUCTION

Heart disease is one of the major causes of death worldwide. According to World Health Organization's report, cardiovascular diseases (CVD) are the number one cause of death globally. More people die annually from CVDs than from any other cause. An estimated 17.3 million people died from CVDs in 2008, representing 30% of all global deaths. Low and middle-income countries are disproportionally affected: over 80% of CVD deaths take place in low and middle-income countries and occur almost equally in men and women [1].

Nowadays, many hospitals use some sort of information systems to manage their healthcare or patient data [2]. Unfortunately, these data are infrequently used to support clinical decision making. The main objective is to develop an Intelligent Heart Disease Prediction System with Quantum Neural Network using heart disease databases to make intelligent clinical decisions which cannot be done in traditional decision support systems.

In this study, we used Quantum Neural Network for the identification of CVD patients and it also predicts the rate of risk. The conventional Neural Network differs from the Quantum Neural Network (QNN) in the form of nonlinear activation functions of their hidden units. A multilevel activation function is used in QNN instead of the ordinary sigmoid function. Each multilevel function consists of the sum of sigmoid functions shifted by the quantum intervals. All models were trained and tested on the test dataset using clinical risk factors.

The major clinical risk factors that are used in our model can be modified, treated or controlled by changing our lifestyle or taking medicine and their normal reference ranges are shown in Table 1.

1.1 Diabetes Mellitus (DM)

Diabetes seriously increases the risk of developing cardiovascular disease. Both major types of diabetes mellitus, Type 1 (insulin dependent) diabetes and Type 2 (non-insulin-dependent) diabetes are associated with a significantly increased risk of coronary heart disease, cerebrovascular disease and peripheral vascular disease [3-8]. Even when glucose (blood sugar) levels are under control, diabetes increases the risk of heart disease and stroke, but the risks are even greater if blood sugar is not well controlled. About three –quarters of people of world population are diabetic. In this situation it is extremely important to work with healthcare provider to manage it. Coronary Artery Disease is a major complication of both insulin – dependent diabetes mellitus (IDDM) and non- insulin – dependent diabetes mellitus (NIDDM). In 14 years of follow- up, the Rancho Bernardo Study, in which 334 men and women with NIDDM were compared with 2137 men and women without diabetes, the relative risk for Coronary Artery Disease deaths was 1.9 in diabetic men and 3.3 in diabetic women compared with non- diabetic men and women after adjustment for other Coronary Artery Disease risk factors [9]. The relation between diabetes and cardiovascular diseases are not uniform in all populations. In the WHO Multinational Study of vascular Disease in Diabetics, the incidence of death in diabetic patients that was attributable to circulatory disease ranged from 32 percent in men and 0 percent in women in Tokyo to 67 percent in men and 47 percent in women in London [10].

Table 1. Reference range of clinical risk factors/ input parameters

#	Clinical risk factor	Lower limit	Average limit	Upper limit
1.	DM	80 mg/dl	140 mg/dl	> 200 mg/dl
2.	LDL	70 mg/dl	130 mg/dl (low Risk)	> 160(High Risk)
3.	HDL	35 mg/dl		80 mg/dl
4.	TG	149 mg/dl	199 mg/dl	499 mg/dl

1.2 Low Density Lipoprotein (LDL)

Low density lipoprotein (LDL) is one of the most fascinating macromolecular assemblies ever evolved by nature and has consequently attracted the attention of scientists for decades. As the principal transporter for cholesterol in the blood, circulating LDL guarantees a constant supply of cholesterol for tissues and cells and is an essential constituent of human life. The cellular uptake of LDL is mediated by specific receptors, either classical B/E receptor or the scavenger receptor pathway [11,12].

1.3 High Density Lipoprotein (HDL)

Abnormality of high density lipoprotein may increase the risk of atherosclerosis. Studies have shown that high-density lipoprotein (HDL) cholesterol levels are a strong, independent inverse predictor of cardiovascular disease [13-17]. According to the Framingham Heart Study, HDL level was considered as more persuasive risk factor for coronary heart disease than the level of low-density lipoprotein (LDL) [16].

1.4 Triglycerides (TG)

High triglycerides raise the risk of heart disease. The American Heart Association (AHA) recommends that a triglyceride level of 100 mg/dL(1.3 mmol/L) or lower is considered "optimal." The AHA says this optimal level would improve heart health. However, the AHA doesn't recommend drug treatment to reach this level. Instead, for those trying to lower their triglycerides to this level, lifestyle changes such as diet, weight loss and physical activity are encouraged. That's because triglycerides usually respond well to dietary and lifestyle changes.

1.5 Related Work

Many risk assessments are based on relatively simplistic strategies, the clinician may identify whether a "risk factor" is present. However, national guidelines advocate the use of scoring systems for CHD risk. Sophisticated methods like the Framingham Risk Score (FRS), the European Systematic Coronary Risk Evaluation (SCORE), the Sheffield risk and treatment table allow calculation of an individual's risk, as a function of the patient's values on selected established coronary heart disease risk factors [18]. The variables used for risk score computation by the different models used, are listed below:

1.6 Framingham Risk Score

The variables used for risk score computation are Gender, age, total cholesterol (TC), HDL, systolic blood pressure (SBP), diastolic blood pressure (DBP), diabetes mellitus (DM), Body Mass Index (BMI) and smoking [18].

The Framingham equations used were developed from cohort data collected in the 1960s and 1970s. We know that since then there has been a fall in the incidence of CHD mortality and a change in the prevalence of smoking. Whilst it may be that the change in incidence is due to the change in the prevalence of risk factors included in the Framingham equation, we cannot be sure that there are not other extraneous factors that have varied over that time and may have affected the incidence of CHD. If so, the validity of the Framingham equation in modern populations may be undermined. For example, some other risk factors such as serum fibrinogen levels, homocysteine, chlamydia infection or any undetected factors may have altered which would distort the Framingham predictions.

1.7 The Joint British Cardiac Society (Bcs)/ British Hypertension Society (Bhs)/ British Hyperlipidemia Association (Bha) Risk Score

The variables used for risk score computation are Gender, age, Total Cholesterol, HDL, Systolic Blood Pressure (SBP), DBP, DM, Smoking, ECG-LVH if available.

1.8 The European Score

The European Heart SCORE model constitutes the basis for national guidelines for primary

prevention and treatment of cardiovascular disease (CVD) in several European countries. The model estimates individuals' 10-year CVD mortality risks from age, sex, smoking status, systolic blood pressure, and total cholesterol level. The SCORE model, however, is not mathematically consistent and does not estimate all-cause mortality [19].

1.9 Finrisk Model

It is based on its European origin. It included Diabetes and LDL [20]. The FINRISK model was derived from the occurrence of acute myocardial infarction or coronary heart disease death during a 10 year follow-up of populations in eastern and southwestern Finland, based on the 1982 and 1987 cohorts.

1.10 Berto Model

The model from Berto and co-workers starts with healthy individuals and model their life until different coronary heartdiseases (CHD) or death by other causes [21]. This model does not go any further after the first CHD event.

1.11 CDC Model

CDC (Centers for disease control and prevention) diabetes cost-effectiveness group made a Markov model which models whether an individual gets CHD or continues to stay "normal". In contrary to e.g. Berto's model, this model doesn't stop at first event, but also models that one can stay in the health states "angina" and "history of CA/MI" for several years.

1.12 Huse Model

Huse and co-workers have, as CDC, modeled up to all individuals are dead [22]. This is however a model which evaluates the difference between different statins. In this model it is possible to start and stop giving medications during the process, which is rather uncommon for models like these.

1.13 Nyman et al. Model

It models the whole process up to death [23]. In this model, all individuals who survive the first year after a cardiovascular event will end up in a "chronic state" and be there until their death.

1.14 Weinstein's Model

This model is possibly the most extensive of those mentioned here [24]. This model has five

health states; persons without CHD, persons with new CHD, persons with CHD, persons who survived up to the age of 85 years, and death. Hence this model has two different absorbing states; survive 85 and death. Individuals in the state "new CHD" will only be there the first year, and after that transfer to "CHD", "survive until 85" or die.

1.15 CANFIS Model

An approach based on coactive neuro-fuzzy inference system (CANFIS) was presented for prediction of heart disease. The proposed CANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach which is then integrated with genetic algorithm to diagnose the presence of the disease. Coactive Neuro-fuzzy modeling was proposed as a dependable and robust method developed to identify a nonlinear relationship and mapping between the different attributes. It has been shown that of Genetic Algorithm (GA) is a very useful technique for auto-tuning of the CANFIS parameters and selection of optimal feature set [25].

2. MATERIALS AND METHODS

2.1 Data Description - Patients Data

The data for this study has been collected from various Hospitals of 689 patients, who have symptoms of heart disease. All these cases are analyzed after careful scrutiny with the help of the Physicians. Table 1 shows the various input parameters for the prediction of heart disease. For training and evaluation purpose we have carefully predicted the level of heart disease by taking the help of Cardiologist/ Physician. The data consists of patients' record with doctor's predictions/ diagnosis. The whole dataset is divided into training, validation and testing as shown in Table 2.

2.2 Proposed Cardiovascular Disease Prediction Systems

This System provides the comprehensive predictive tool for predicting cardiovascular disease; this system predicts the cardiovascular disease in early stage by clinicians, doctors, pathologists as well as by general public also, may predict the chances of having the cardiovascular diseases using the important Clinical tests caused for cardiovascular disease, so that the clinicians may fulfill their promises and

Table 2. Data Partition Set

#	Data partition set	Records	Percentage
1	Training set	189	27.44
2	Validation set	250	36.28
3	Test set	250	36.28
4	Total	689	100.00

commitments for ensuring sustained fight against this deadly disease. The major Clinical factors are considered for prediction, which have not been considered altogether in any system, developed so far.

2.3 Quantum Neural Network Used for Cardiovascular Disease Prediction System

Quantum Neural Network based on multi- level transfer function was introduced by Karayiannis et al. The major difference between conventional neural network and quantum neural network is the form of the nonlinear activation functions of their hidden units. The activation function of quantum neural network express as linear superposition of multi-sigmoid function. Various models of Quantum Neural Network based on Multi-level transfer function have been used in the prediction of weather, disease diagnosis and voice recognition [26,27,28]. In such manner, more states are expressed in a hidden layer neural cell in comparison to traditional sigmoid function. The quantum interval for each sigmoid function is different. It is obtained by training of quantum neural network. The model of Quantum Neural Network is useful in the indetermination and crossed pattern problem. Multilevel transfer function of neural cell in hidden layer represents the feature of fuzziness. It's effective to classify indeterminate data.

2.4 Algorithm for Training the Quantum Neural Network

The QNN used for our proposed system consists of input, output and hidden units, as shown in Fig. 2. Here, only one hidden layer has been used. In our proposed system, the QNN's every node of hidden layer represents only three sub states in itself with the difference of quantum interval θ^r with quantum level r. Here more than three sub states may be possible in every node of hidden layer, but with every additional sub state the computational complexity increases, but for our proposed system, with three sub states the performance of QNN is optimum with significant accuracy. Let us assume that n_s

denotes the number of grades or excitation levels, η is learning rate which is a small random value, δ_k is error rate of output layer and δ_j error rate of hidden layer. Where n_i denotes the input to the input layer. O_j and O_k denotes the output of hidden and output layer, respectively. The weights between input and hidden layers are denoted by W_{ij} and the weights between hidden and output layers are denoted by W_{kj}. The initial weights are small random numbers and t denotes Target value. First apply the inputs to the network and calculate the output [29,30,31].

Given R training pairs {n_1, t_1; n_2, t_2; n_R, t_R}

Where n_i(J X 1) is input and t_i (K X 1) is target values for given inputs, for the present quantum neural network as shown in Fig. 1.

The error signal term of the output (δ_k) and hidden layers (δ_j) are written as,

$$\delta_k = (t_k - O_k)\, O_k\, (1 - O_k) \quad \text{\{k=1, 2, 3...., K\}} \quad (1)$$

$$\delta_j = O_j (1 - O_j) \sum_k W_{kj}^{New} \delta_k \quad \text{\{j=1, 2, 3...., J\} and \{k=1, 2, 3...., K\}} \quad (2)$$

Consequently, output layer weights (W_{kj}^{New}) and hidden layer weights (W_{ji}^{New}) are adjusted as.

$$W_{kj}^{New} = W_{kj}^{old} + \eta \delta_k O_j \quad \text{\{j=1, 2, 3...., J\} and \{k=1, 2, 3...., K\}} \quad (3)$$

$$W_{ji}^{New} = W_{ji}^{old} + \eta \delta_j O_i \quad \text{\{i=1, 2, 3...., I\} and \{j=1, 2, 3...., J\}} \quad (4)$$

The simple sigmoid function has been used as the activation function from input to hidden layer and is expressed as:

$$sgm(x) = \left(1/(1 + \exp(-x))\right) \quad (5)$$

The sigmoid function with various graded levels has been used as the activation function for each hidden neuron i.e. from hidden to output layer is expressed as follows:

$$sgm(x) = \sum_{r=1}^{n_s} \left(1/(1 + \exp(-x + \theta^r))\right)$$

(6)

Here the initial value of θ^r is initialized by zero, then apply Eq1 to 6 and iterate this process several times upto i iterations until it reaches the lowest possible error and then apply Eq 7.

After i iterations when minimum possible error is obtained, then increase in quantum interval by very small quantum interval $\Delta\theta$, for this proposed system we have used the value of $\Delta\theta$ is 0.25.

$$\theta^r = \theta^r + \Delta\theta$$

(7)

Repeat this step until δ_k is decreased to an acceptable accuracy.

3. RESULTS AND DISCUSSION

The proposed system predicts the rate of heart disease or the percentage rate of disease on the basis of Clinical risk factors; it also predicts the future condition in advance. The Proposed system is based on Quantum Neural Network, means it is predictive as well as adopts the predictive knowledge based on the past experience i.e. on the basis of past data it learns, and gradually maximizes the accuracy level of prediction. We have categorized the risk level into

four groups according to percentage level as Normal, Low Risk Range, Intermediate risk range and highest risk range. The percentage for each level is shown in Table 3.

The results of our experimental analysis for significant patterns for cardiovascular disease prediction using Clinical risk factors are presented in this section. In this work, we have only used Clinical risk factors significant to cardiovascular Disease. After analysis of patients' data, the patients may be categorized on the basis of reference range. As shown in the Fig. 1, the total numbers of patients are distributed percentage wise patient distribution lies in Lower, Average and High Level Reference rangeof Diabetes Mellitus (DM), Low Density Lipoprotein (LDL), Triglycerides (TG) and High Density Lipoprotein (HDL).With the help of the dataset, the patterns significant to the cardiovascular disease prediction are extracted. The dataset is divided into training set, validation set and test set as shown in Table 2.

Table 3. Percentage level of risk categories

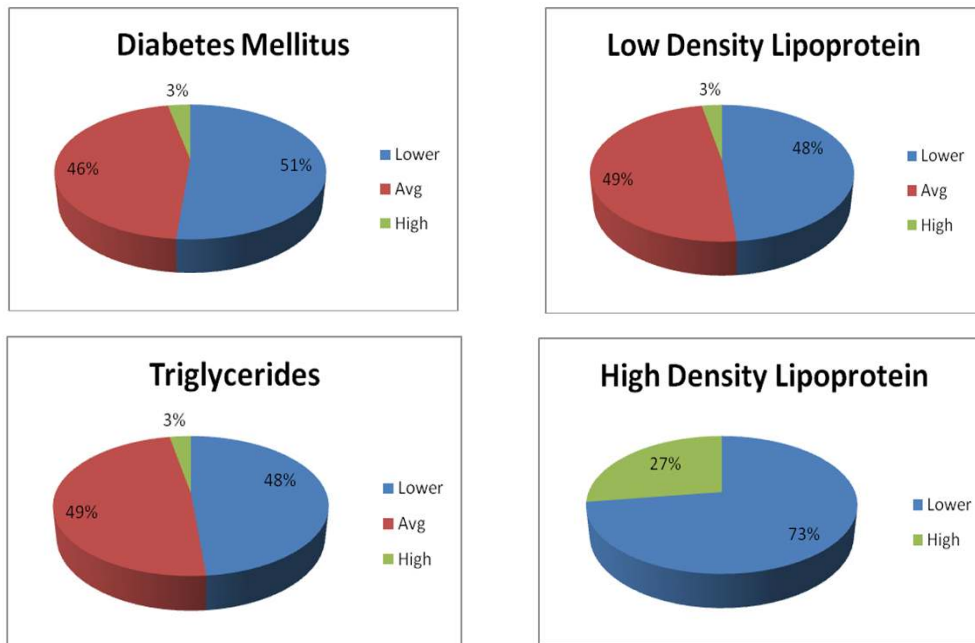| Risk category	Percentage
Normal	Below 26
Low risk range	26-51
Intermediate risk range	51-76
Highest risk range	76 and above

Fig. 1. Percentage wise patient distribution under lower, average and high level reference range

The Quantum Neural Network is trained with the selected significant patterns. The architecture of the quantum neural network used in this study is having 4 input nodes, 15 hidden nodes and 1 output nodes as shown in Fig. 2.

The Quantum Neural Network is trained with the above mentioned number of nodes and accuracy graph is shown in the Fig. 3 and its performance graph is shown in Fig. 4. The number of input nodes is determined by the clinical parameters, the number of hidden nodes is determined through tuning; and the number of output node is

represented as percentage level of cardiovascular disease.

The proposed work shows that the prediction of risk from cardiovascular diseases gives best results on the dataset used. The result generated by this system has been evaluated and validated on data of patients with the Doctor's diagnosis (predictions). When the QNN is trained and tested after optimizing the input parameters, the overall predictive accuracy obtained is 96.97%. Data Showing Prediction accuracy of Random Testing on different Experimental values has been given in Table 4.
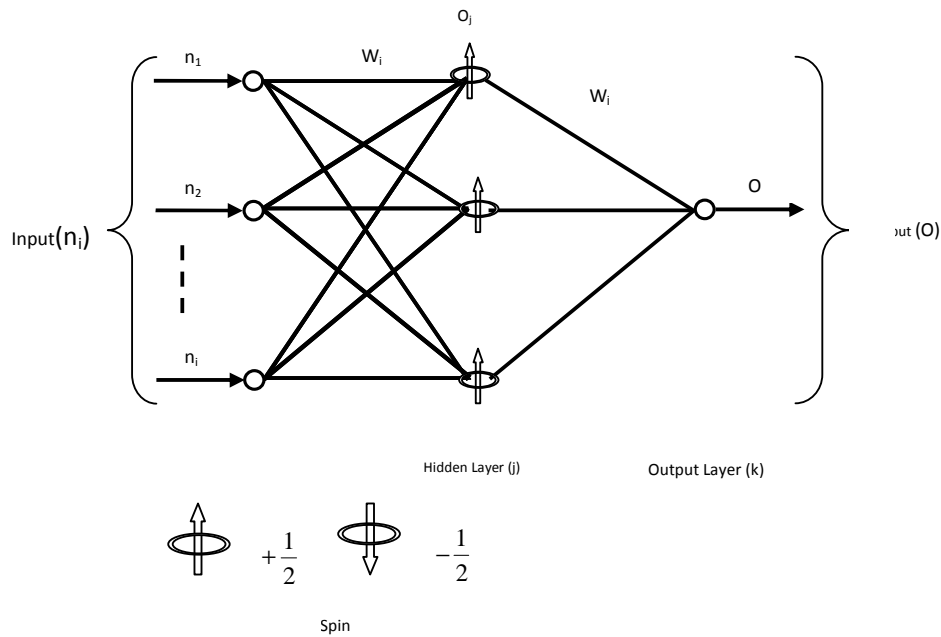

Fig. 2. Architecture diagram of quantum neural network for cardiovascular disease prediction system
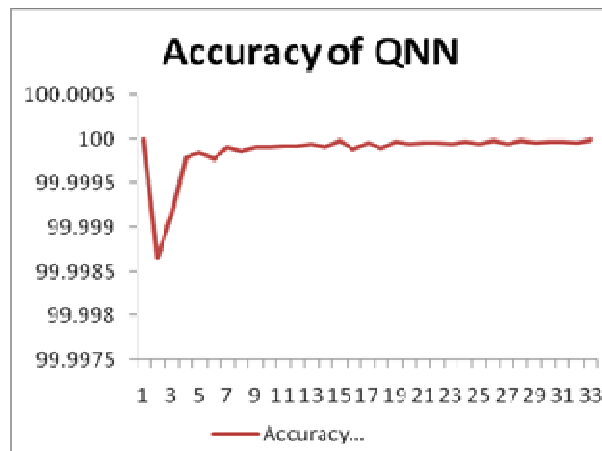

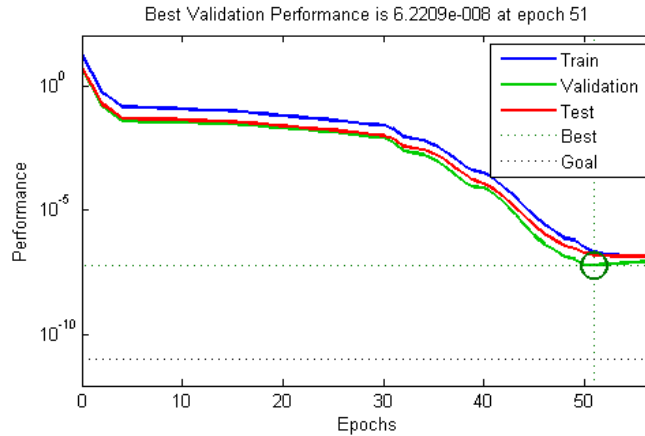**Fig. 3. Graph showing accuracy of CVD prediction system based on QNN**

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Fig. 4. Performance graph of quantum neural network

Table 4. Data showing prediction accuracy proposed on different experimental values

Diabetes	LDL	HDL	Triglycerides	Equated/ Calculated desired result		Desired result based on Doctor's diagnosis	Result and accuracy of proposed QNN based system	
				Output	Risk Cat.		Output	Risk Cat.
151.25	135.63	52.5	255.25	59.38	Int	Int	59.38	Int
121.25	111.25	72.5	183.38	34.38	Low	Low	34.38	Low
188.75	154.38	27.5	442.75	90.63	High	High	90.63	High
95	85	90	161.5	12.5	Nml	Nml	12.5	Nml
80	70	100	149	0	Nml	Nml	0.02	Nml
201	160	20	499	100	High	High	100	High
117.5	107.5	75	180.25	31.25	Low	Low	31.25	Low
143.75	131.88	57.5	217.75	53.13	Int	Int	53.13	Int
113.75	103.75	77.5	177.13	28.13	Low	Low	28.13	Low
91.25	81.25	92.5	158.38	9.38	Nml	Nml	9.38	Nml
196.25	158.13	22.5	480.25	96.88	High	High	96.88	High
139	130	60	199	50.45	Low	Low	51	Int
162.5	141.25	45	311.5	68.75	Int	Int	68.75	Int
83.75	73.75	97.5	152.13	3.13	Nml	Nml	3.13	Nml
192.5	156.25	25	461.5	93.75	High	High	93.75	High
106.25	96.25	82.5	170.88	21.88	Nml	Nml	21.88	Nml
128.75	118.75	67.5	189.63	40.63	Low	Low	40.63	Low
166.25	143.13	42.5	330.25	71.88	Int	Int	71.88	Int
181.25	150.63	32.5	405.25	84.38	High	High	84.38	High
87.5	77.5	95	155.25	6.25	Nml	Nml	6.26	Nml
185	152.5	30	424	87.5	High	High	87.5	High
155	137.5	50	274	62.5	Int	Int	62.5	Int
132.5	122.5	65	192.75	43.75	Low	Low	43.75	Low
125	115	70	186.5	37.5	Low	Low	37.5	Low
177.5	148.75	35	386.5	81.25	High	High	81.25	High
170	145	40	349	75	Int	Int	75	Int
98.75	88.75	87.5	164.63	15.63	Nml	Nml	15.63	Nml
136.25	126.25	62.5	195.88	46.88	Low	Low	46.87	Low
110	100	80	174	25	Nml	Nml	25	Nml
158.75	139.38	47.5	292.75	65.63	Int	Int	65.63	Int
173.75	146.88	37.5	367.75	78.13	High	High	78.13	High
102.5	92.5	85	167.75	18.75	Nml	Nml	18.75	Nml
147.5	133.75	55	236.5	56.25	Int	Int	56.25	Int

*Risk Cat.: Risk Category, Nml: Normal, Int: Intermediate, High: Highest

4. CONCLUSION

The proposed work shows that the prediction of risk from cardiovascular diseases gives best results based on clinical factors. The result generated by this system has been evaluated and validated on data of patients with the Doctor's diagnosis (predictions). This proposed system will help the doctors to plan for a better medication and provide the patient with early diagnosis as it performs reasonably well even without retraining. The QNN has been trained and tested after optimizing the input parameters. The optimization has been done by selecting minimum distorted data set of input parameters. The overall predictive accuracy obtained was 96.97%.Data Showing Prediction accuracy of Random Testing on different Experimental values has been given in (Table 4). Hence the proposed system will work as a significant tool for doctors/ practitioners.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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