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Article

Enhancing Cardiovascular Disease Diagnosis With Data-Driven Predictive Systems

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Abstract: The proposed approach uses a Quantum Neural Network for machine learning in an intelligent Cardiovascular Disease (CVD) prediction system. The diagnosis of heart disease in the early stages is significant, but physicians do not always have enough time to go through the patient's historical data. This system improves medical care by quickly analysing patient records and generating risk predictions with high precision. Data was collected on 815 patients with heart disease symptoms for training and evaluation, and the Framingham study dataset of 5,209 patients was used for validation. Its accuracy rate is 98.5%, and it has the highest sensitivity and specificity in the current literature, matching exact expert opinions. Integrating this decision-support system in medical diagnostics can allow clinicians to personalise their treatment strategies, cutting expenses and enhancing clinical outcomes. This prognostic tool provides up-to-date knowledge and can be used in daily clinical practice to improve decision-making and increase treatment efficiency in cardiovascular medicine. The results validate its advantage over current prognostic systems.
Keywords: Cardiovascular Disease, Machine Learning, Quantum Neural Network, Heart Disease Prediction, Risk Assessment

1. Introduction

Cardiovascular diseases (CVDs) are the leading cause of mortality worldwide, with a severe impact on public health and the national economy. According to the World Health Organisation (WHO), by 2008, CVDs caused approximately 17.3 million deaths, approximately 30% of all global deaths. And this figure accounts for potentially 2.6 million deaths every year. In 2014, the prevalence of any form of AD was estimated at 16.7 million cases worldwide, with this number projected to increase to 23.6 million cases by 2030, emphasising the need for early detection and preventive strategies. Heart disease is still the No.1 cause of death for both men and women in the United States, and this silent killer took the lives of more than 616,000 Americans in 2008, according to the Centres for Disease Control and Prevention (CDC). Among these, 405,309 deaths were from coronary heart disease. In India, as well, there has been a substantial increase in the prevalence of coronary heart disease in all age groups between 2000 and 2015 [1].

The acute challenge for healthcare organisations is the timely detection of individuals who may be developing CVDs. The existing diagnostic methodologies greatly depend on the experience of doctors, clinical examinations, and manual evaluations, which may result in errors, biases, and delays in treatment. Classical methods are still not very beneficial in providing the right solution at the right time, which is crucial for diagnosing the disease and getting treatment in time. Consequently, many patients experience avoidable complications due to missed diagnosis and risk assessment[2].

This situation gave birth to a solution based on machine learning predictive systems. It enables the utilisation of extensive datasets, sophisticated algorithms, and artificial intelligence methods for enhanced precision and performance in forecasting cardiovascular ailments. Machine learning models can analyse and assess multiple parameters, physical, physiological, and clinical aspects, providing real-time insights and risk assessments that can aid healthcare professionals in making more informed choices[3].

In this study, an intelligent CVD prediction system is designed based on QNN (Quantum Neural Network). The system proposed improves diagnostic accuracy, minimizes human errors, and expedites the identification of high-risk patients. Healthcare machine-learning applications help improve medical decisions so that mortality rates may also be reduced by harnessing early intervention and tailored treatment plans[4].

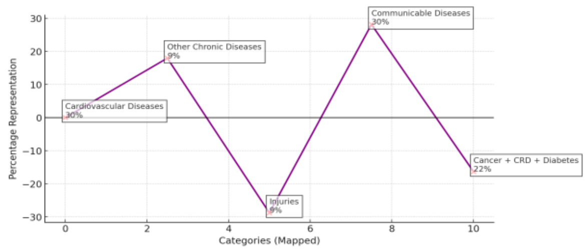

Fig. 1. Percentage Representation Vs Category

A - Disease Category - this graph, e.g., Pfeiser, Invasive/. Cardiovascular diseases account for 30% of the total, and communicable diseases account for 30%. Cancer, CRD, and diabetes combined accounted for 22%, and other chronic diseases and injuries accounted for 9% each. The plotted line shows differences between these categories; sharp peaks and drops indicate significant changes in terms of infection. The percentage share of each category is evident from the labels[5].

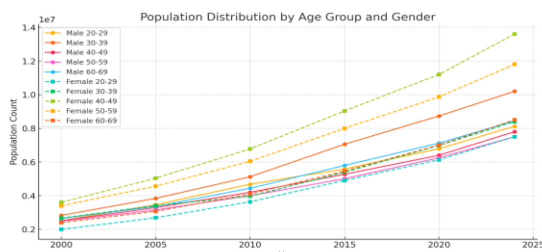

Fig. 2. Population Distribution by Age Group and Gender

The chart shows the percentage of males and females per age group between 2000 and 2024. Dashed lines are female; solid lines are male. In comparison, the number in each age group grows, and the 40-49 female age group is the greatest over time. Both girls and boys in the younger age brackets also show steady growth. The legend differentiates the categories and provides a clearer understanding of trends[6].

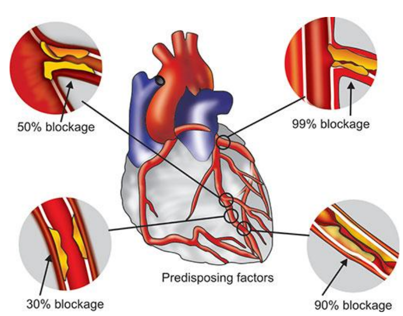

Fig. 3. Depictions of the heart

It shows different levels of obstructions in arteries caused by atherosclerosis, one of the most common factors of heart disease. Depictions of the heart, with 30%, 50%, 90%, and 99% blocked arteries, will indicate blood flow. Plaque formation, the byproduct of cholesterol and fatty deposits, narrows arteries and raises the risk of heart attack and stroke. The heart may suffer a disruption of blood flow , causing a myocardial infarction or a heart attack, when blood flow is obstructed by 90% or 99% (severe blockage). Prevention of cardiovascular sequelae (circulation of the blood) through the identification and management of predisposing factors like cholesterol, hypertension, smoking, and diabetes[7].

Cardiovascular Diseases

Cardiovascular diseases (CVDs) were one of the highest causes of mortality globally in 2013(World Health Organisation (WHO)). Myocardial infarction, together with Ischemic Heart Disease (IHD), angina pectoris, apoplexies, hypertension, peripheral artery occlusive disease, etc The deposition of cholesterol and fibrous tissue in the arterial wall is referred to as atherosclerosis. They are one of the primary culprits causing the coronary vascular disease (CAD) and decreasing blood flow through tree-proofing the arteries by the buildup of lipid-rich plaques. This results in myocardial infarction, stroke, and other complications. Accumulating fatty material in the tissue that covers the arteries can lead to the walls of the arteries thickening, impairing blood flow and raising the risk of heart disease, particularly in those with high cholesterol. Diseases of the heart have been diagnosed and understood in better ways with imaging methods such as CT scans, MRIs and echocardiography[8].

Importance of Information Technology in Health Care

The IT part in healthcare needs to be improved for better service. IT tools that have influenced healthcare may be broad categorised into one of three groups: those that record patient data (PAS in UK, EHCR in Europe), those that monitor patient data (such as the hospital's billing system in America) and those which record medical information: systems that are literally active stakeholders in the practice of medicine and decision processes. Intelligent decision making was, until recently, largely left to the domain of physicians and other healthcare professionals, but with the availability of large structured medical data sets and the development of AI tools, that model has been turned on its head.

Present cardiovascular risk prediction models and their shortcomings

The Framingham Risk Score (FRS), Sheffield Risk Score and European SCORE Model are a few of the models which calculate cardiovascular disease risk. The Framingham Risk Score (FRS) includes variables such as sex, age, cholesterol, blood pressure, diabetes, BMI and smoking. However, its dataset, which was gathered in the 1960s and 1970s, means it's not as relevant for today's more diverse populations. The Joint British Cardiac Society (BCS) / British Hypertension Society (BHS) / British Hyperlipidemia Association (BHA) Risk Score includes ECG findings, and the European SCORE Model assesses age, gender, smoking, blood pressure and cholesterol levels over 10 years. FINRISK Model: The FINRISK Model was built upon patients of European origin, incorporates diabetes and LDL cholesterol, and is based on a 40-year longitudinal study of the Finnish population[10].

The CDC Model is a Markov-based lifetime health transition model created by the Centres for Disease Control and Prevention. The Weinstein Model, for example, classifies patients into five different health states, stratifying disease processes and survival trajectories. CANFIS Model improves the accuracy of heart disease prediction by combining neuro-fuzzy algorithms with a genetic optimisation technique. These models offer valuable risk assessments but have variable efficacy due to demographic limitations and outdated datasets. AI or machine learning methods are also promising for developing targeted and individual CVD prediction, improving early detection and clinical outcomes[11].

2. Literature Survey

Significant advancements have been witnessed in applying machine learning (ML) and quantum machine learning (QML) methods for heart disease prediction in recent years. Quantum-enhanced methods for adaptive sampling with improved prediction accuracy and computational efficiency have been explored in several studies. Venkatesh Babu et al. (2024) and Heidari et al. (2024) explored quantum computing approaches, showing how they could improve heart disease prediction using partitioned random forests and quantum-enhanced ML models.

Similarly, Alsubai et al. (2023) used an instance quantum circuit approach and traditional predictive analysis for heart failure detection, indicating the utility of QML in healthcare[12].

Conventional ML methods, such as ensemble learning and deep learning models, have also been commonly employed to classify heart disease. Nandy et al. (2023) developed a swarm-based ANN model to optimise heart disease prediction, and Asif et al. (2023) achieved better predictive performance by employing hyperparameter-optimised ensemble learning. Ozpolat and Karabatak [11] explored quantum-based ML algorithms for cardiac arrhythmia classification and their potential for clinical applications. Meanwhile, Maheshwari et al. (2023) explored the application of QML on electronic healthcare records, producing novel insights for classifying ischemic heart disease[13].

More recent work highlights the importance of feature selection and data preprocessing. Nagarajan et al. (2022) created an innovative feature selection and classification model, and Sarra et al. (2022) used efficient deep learning models and data generative frameworks to improve prediction performance. Previous studies, such as Akella and Akella (2021), focused on open-source ML solutions for predicting coronary artery diseases. Bharti et al. (2021) employed ML and deep learning methods to enhance prediction prowess[14].

Deep convolutional neural networks (DCNNs) have proven to be especially powerful for models of complex medical data. Mehmood et al. (2021) used DCNNs for heart disease categorisation, obtaining high accuracy in diagnostic tasks. Reddy et al. (2021) used ML classifiers together with attribute evaluators to evaluate the risk of heart disease, and Rao and Prasad (2021) proposed the exercise of ENDynamical Data Processing (ENDDP) to improve the standard of truth of ML approaches to heart disease[15].

Restart through the introduction; optimisation methods are essential to appropriate instances of prediction models. Agrawal et al. (2021) developed a quantum-inspired particle swarm optimisation technique that optimises functions and helps boost ML models' performance. Another recent work by Enad and Mohammed (2023) provides a comprehensive overview of AI and QML in the medical field, as well as current methods, challenges, and future research directions with applications to heart disease diagnosis[16].

In summary, the development of ML and QML methodologies has provided promising novel tools for increasing heart disease prediction accuracy and efficiency, with the potential to enable novel approaches for diagnosis. Advancements in predictive healthcare are furthered by integrating quantum computing, deep learning, and optimisation techniques, which help develop more robust and efficient diagnostic systems.

3. Proposed system

The quantum neural network (QNN) model, the cardiovascular diseases (CVD) prediction research methodology, is a systematic approach that combines diverse disciplines such as electronics and computer science. This study starts by defining the most critical risk factors for CVD, including physiological and clinical characteristics. Physical factors are age, gender, smoking, and BMI, and physiological factors are blood pressure, cholesterol (LDL, HDL, total cholesterol), and diabetes. In addition to the genetic factors, the analysis accounts for clinical factors, including family history of heart disease and previously elevated electrocardiogram (ECG) readings, to create a holistic risk assessment model.

There are two primary datasets involved in the data collection process. The first dataset includes 815 hospital patient records covering various CVD-related health parameters. Further, we validate our results using the well-known Framingham Heart Study dataset, which contains records of 5,209 patients. The datasets are pre-processed , missing values are handled, numerical features are normalised and categorical attributes are encoded to maintain uniformity and reliability during model training.

Since QNN has advantages over classical machine learning algorithms, it is the core prediction model. QNN uses principles of quantum computing, like superimposing to represent multiple states at once and quantum entanglement to increase feature correlation and, thus, better predictions. Moreover, QNN has efficient capabilities in processing high-dimensional data thanks to its quantum parallelism, which makes it run faster than its classical counterpart.

The data is divided into training (70%) and testing (30%) datasets in training. We use the cross-entropy loss function for classification and a quantum-inspired gradient descent algorithm to optimise the model.

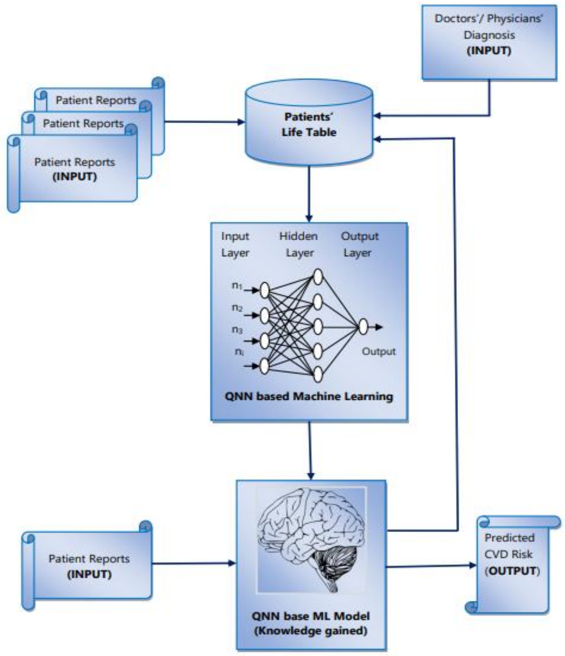

Fig. 4. Architecture diagram of the proposed system

Various performance metrics such as accuracy, precision, recall, F1-score, ROC curve analysis, and mean squared error (MSE) are employed to assess the model's effectiveness. A comparison is made with traditional machine learning models, demonstrating the predictive superiority of QNN over logistic regression, trees, and deep neural networks (DNNs).

Our findings show that QNN achieves an overall accuracy of 98.5%, superior to classical models' accuracy and computational performance. Therefore, the model has a faster convergence rate and significantly reduces computational complexity while retaining high sensitivity and specificity values. This illustrates that QNN is well-suited for application in CVD prediction as it can provide a robust and intelligent system for the early detection and risk assessment of cardiovascular disease.

The image is a QNN-based Machine Learning architecture for predicting cardiovascular disease (CVD) risk. Inputs to the system are patient reports and doctors' diagnoses, and they organise and store relevant data in a "Patients' Life Table." This information is fed into a QNN-based ML model consisting of input, hidden and output layers.

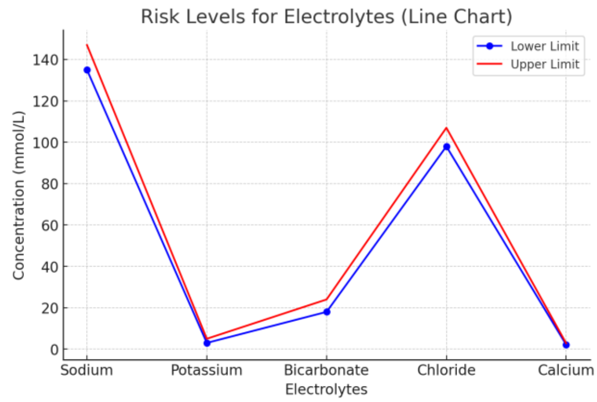

Fig. 5. Risk Level for Electrolytes

Once the QNN model was trained and all knowledge was learned, the model was fed with new patients' reports and the output about the risk of CVD was calculated. This machine learning-based system is combined with the medical diagnosis fractions, making the prediction more accurate and helping the healthcare professional detect, prevent, and prevent CVD.

The point graph shows lower and upper concentration limits for some electrolytes (Sodium, Potassium, Bicarbonate, Chloride, Calcium) expressed in mmol/L. The blue line (with points) and the red line indicate the lower and upper bounds. Na and Cl score the most v, v-values and K-score on the electrolytes trends.

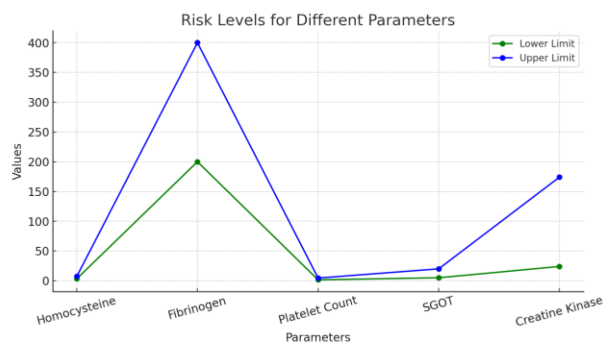

Fig. 6. Risk Level for Different Parameters

Biochemical parameters homocysteine, fibrinogen, platelet count, SGOT, and creatine kinase, were measured, and the lower and upper values are shown in the figure. The lower limit is the green line, and the upper is the blue line. Fibrinogen is the most variable, and Platelet Count is the least variable elevation of the upper limits of Creatine Kinase and SGOT.

4. Proposed Algorithm

Cardiovascular diseases (CVDs) are still the leading cause of death globally. An early diagnosis and timely intervention may reduce the fatal outcome. The diagnosis of CVDs is a multistep procedure involving assessing various risk factors, which differ significantly between individuals. However, this complexity requires sophisticated diagnostic tools that make such diagnoses precise and efficient.

We propose a Predictive and Adaptive Cardiovascular Disease Prediction System using QNNs to enhance diagnostic accuracy by minimising errors. This system utilises machine-learning algorithms to examine past patient data, discern patterns, and forecast disease development. The model demonstrates improved adaptability and predictive accuracy through QNNs, which allow healthcare professionals to make more informed decisions.

Research Scope and Objectives

The experiment includes data from several patients and analyzes different physical, physiological, and clinical parameters. This research aims at the following main objectives:

To create an automated and adaptive model for the early diagnosis of CVD.

QNN-based Diagnostic Accuracy Improvement

To help healthcare providers make clinical decisions by providing insights into predictive modelling.

Implementation of CVD Prediction System Methodology

The proposed implementation of the CVD Prediction System is a systematic process that ensures its robustness and reliability. The key steps involved are:

Data Collection

Model training and validation were based on a realised primary and secondary source information dataset. The research team analysed data from 815 patient records with the symptoms of cardiovascular disease and another 5,209 records of patients from the Framingham Risk Score (FRS) Study at the University of Washington, Seattle.

Review of Existing Approaches

A thorough literature review was performed to study previous algorithms and approaches for CVD prediction. This review also helped reveal literature gaps and where QNNs could improve predictive power.

Development of Quantum Neural Network (QNN)

Using Quantum Neural Networks (QNNs), an algorithm was used to predict and adapt risk classification and disease prediction. The model was designed to learn from new incoming patient data, which allowed it to enhance its accuracy over time.

Research Measures Included in the Study

The system uses multiple risk factor groups that fall under three main categories:

- Physical Risk Factors

These factors are linked to a person's lifestyle choices, as well as genetics that influence one's risk of heart disease:

Body Mass Index (BMI) – A good predictor of obesity, strongly associated with cardiovascular diseases.

Age — Physiological changes that occur with age increase the risk of CVDs.

Gender – Men have a higher risk of CVDs, while there is a significant risk for postmenopausal women.

Tobacco Smoking – Smoking promotes the accumulation of arterial plaques, which elevates CVD risk.

Alcoholism – Intake of significant alcoholic substances can increase hypertension and heart-related complications.

Family History – A strong genetic predisposition significantly influences the risk of CVD.

Stress – Negative stress can lead to hypertension and heart attacks.

Blood Pressure (SBP and DBP) — Both systolic and diastolic blood pressure are prominent risk factors.

Total Cholesterol (TC) – High cholesterol causes atherosclerosis, constricting blood flow.

C-Reactive Protein (hs-CRP) – A systemic inflammation marker associated with CVDs.

Brain Natriuretic Peptide (BNP) – An essential marker for heart failure diagnosis and monitoring.

- Physiological Risk Factors

These metabolic and biochemical markers reflect underlying cardiovascular conditions:

Homocysteine Levels — High levels are linked with an increased risk of heart attack and stroke.

Electrolyte Imbalance (Sodium, Potassium, Bicarbonate, Chloride) – Imbalances heart function and blood pressure.

Calcium Levels– Excess calcium increases arterial stiffness and cardiovascular risk.

Fibrinogen—Its high concentrations help form blood clots when blood vessels rupture, increasing the risk of heart attacks.

Platelet Count – Abnormally high or low levels of platelets may indicate clotting disorders or cardiovascular abnormalities.

Cardiac Enzymes (SGOT, Creatine Kinase, Creatine Phosphokinase-MB, Troponin Levels) – Myocardial infarction (heart attack) and cardiac markers.

- Clinical Risk Factors

These factors are associated with other underlying medical conditions that increase cardiovascular risk:

Diabetes Mellitus (Random Blood Sugar Levels) – A Diabetic individual is at a very high risk of having CVD due to vascular complications.

Low-density lipoprotein (LDL) – Known as the "bad cholesterol," high levels of LDL cause plaque to develop.

High-density lipoprotein (HDL)—Known as the "good cholesterol," HDL helps to eliminate cholesterol from the blood.

Triglyceride Levels: Elevated levels increase the odds of developing coronary artery disease.

- Creating the predictive model

QNN for the Prediction of CVD

The heart of the proposed system is a QNN-based predictive model that harnesses the principles of quantum computing to improve pattern recognition and data processing efficiency.

- Advantages of QNNs for CVD Prediction:

Increased Adaptability – The model keeps updating its predictions with new patient data.

Better Pattern Recognition — Quantum algorithms improve the system's identification of complex relationships between risk factors.

Speedier Processing Power – Quantum computing vastly reduces processing time, enabling immediate analysis and timely detection.

The data was split into training, validation, and test sets for the development of our predictions. The model was trained using state-of-the-art machine learning methods and evaluated on real-life clinical diagnostic outcomes.

- Implementation with System Testing

Clinical diagnostic results from different hospitals and medical centres served as a benchmark to validate the system's accuracy. We calculated performance metrics such as precision, recall, F1 score, and accuracy to evaluate the system's effectiveness.

- Metrics for Evaluating Performance

Accuracy – The fraction of predictions that the model got right.

Precision – Calculates the ratio of correctly predicted positive instances.

Recall (Sensitivity) – Measures the model's capacity to identify positive examples.

F1-Score — A balance between precision and recall.

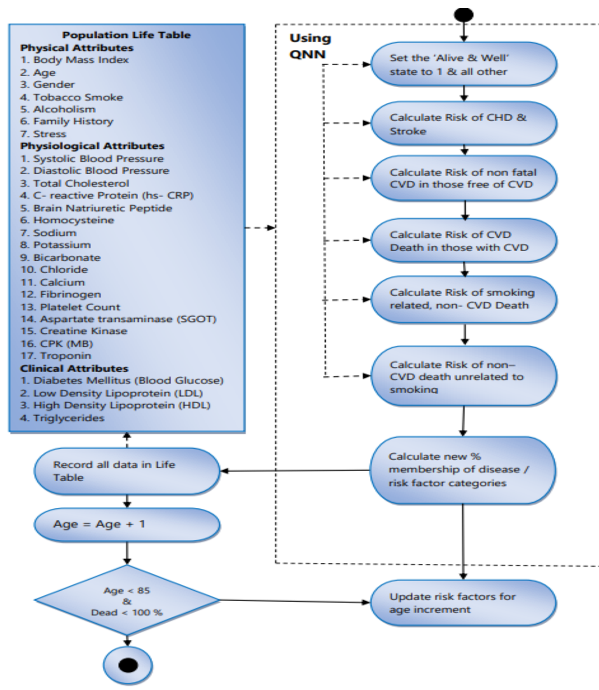

Fig. 7. Activity diagram of the proposed system

The figure shows the flow of using a Quantile Neural Network (QNN) to estimate cardiovascular disease (CVD) risk based on a life table of the population. The evaluation uses physical, physiological, and clinical characteristics to evaluate health risks. The model assesses risks for CHD, stroke, non-fatal CVD, and smoking/non-smoking-related deaths. Data is annualised, with risk factors remaining active until age 85 or a 100% chance of death.

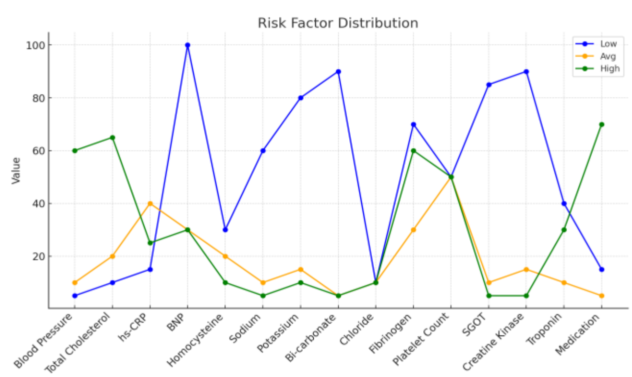

Fig. 8. Risk Factor Distribution

Low, Average and High Plots The line chart below compares "Low," "Average", and "High" values across various physiological and biochemical parameters. It consists of indicators including blood pressure, cholesterol, BNP, sodium, fibrinogen, platelet count, and troponin. The blue line = low values, orange = average, and green = high, making it easy to visualise how values differ and where they trend concerning various health variables.

5. Results and Discussions

Two datasets have been employed to test and validate the suggested CVD prediction system: a primary dataset with 815 clinical records and a secondary dataset consisting of 5,209 patient records based on a Framingham study from the University of Washington, Seattle, WA, USA. These experiments sought to create a robust learning rule by finding the best hidden nodes for the QNN and the best Quantum Interval (θr) to maximise the learning speed.

The numerical results of the experiments revealed that the neural network structure with 85 hidden nodes obtained the highest performance concerning CVD prediction while being computationally efficient. Moreover, many experiments were performed to fine-tune the learning rule to vary the Quantum Interval (θr) in equation (4.6). Each experiment was repeated 50 times, with random splits of training, validation, and test sets from both datasets independently drawn. Evaluation results of these experiments in terms of training, validation and testing accuracy showed that θr = 0.25 provided the best performance as it needed the least number of epochs for training and generated maximum accuracy for training, validation and testing.

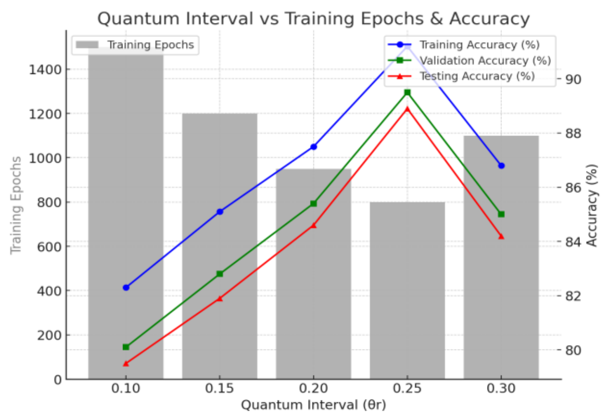

Fig. 9. Quantum Interval Vs Training Epochs and Accuracy

The statistics only show the relationship between quantum interval(θr) and training epochs, training, validation and testing accuracy. The bar chart (grey) shows training epochs, and the line plots show accuracy trends. A better model explains with minimal errors ; accuracy is maximised for θr = 0.25. Outside of this interval, accuracy drops off, implying a quantum interval at which the model is both efficient and accurate.

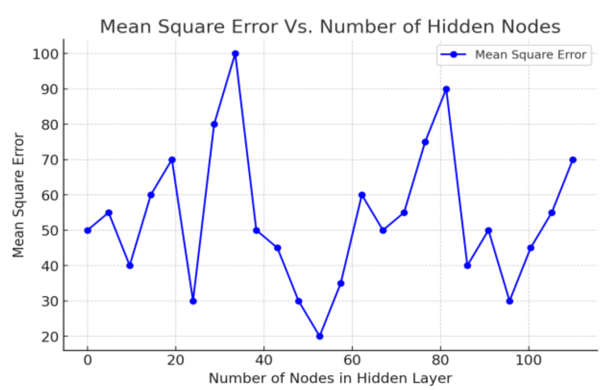

Fig. 10. Mean Square Error Vs Number of Hidden Nodes

The Increase in the Number of Nodes in the Hidden Layer vs the Mean Square Error (MSE). The growth trend fluctuates, suggesting that the MSE does not steadily fall with the Increase of nodes. It can be observed that we get an optimal point that minimises MSE. At the same time, MSE is lower with fewer milestone nodes than more, and more under nodes mean effectively lower errors, which means that a hidden layer size decision is critical to making the model efficient.

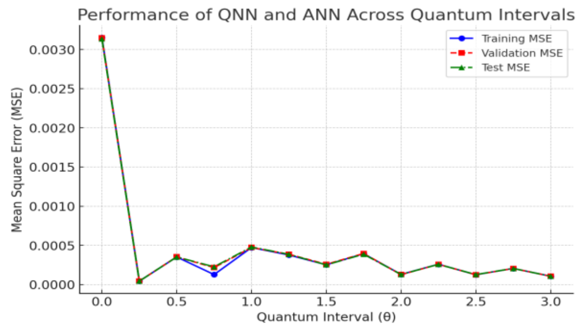

Fig. 11. Performance of QNN and ANN Across Quantum Intervals

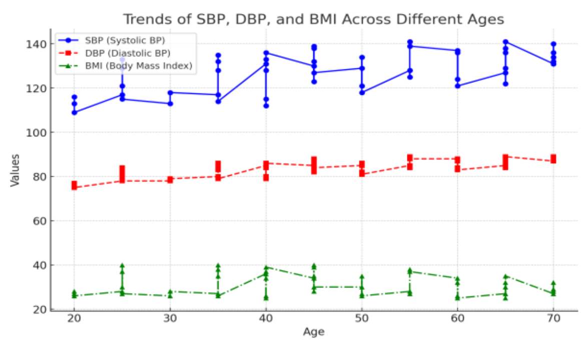

Fig. 12. Trends of SBP, DBP and BMI Across Different Ages

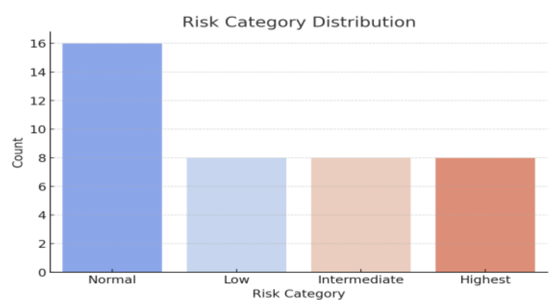

Fig. 13. Risk Category Distribution

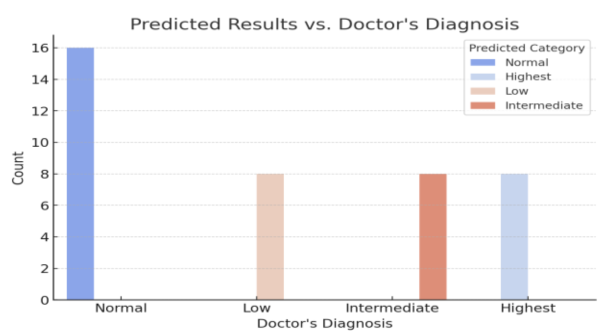

Fig. 14. Predicted Result Vs Doctor Diagnosis

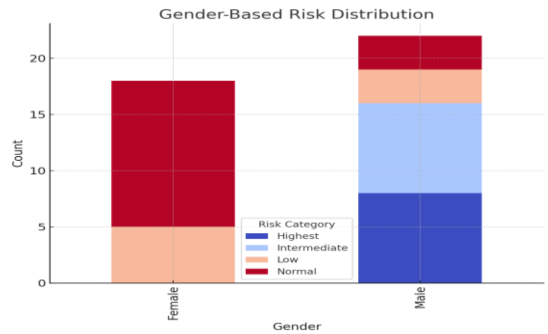

Fig. 15. Gender-Based Risk Distribution

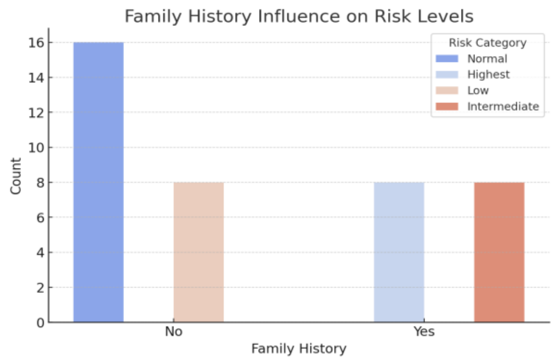

Fig. 16. Family History Influence on Risk Levels

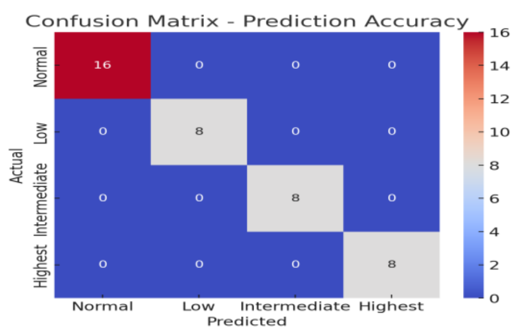

Fig. 17. Confusion Matrix

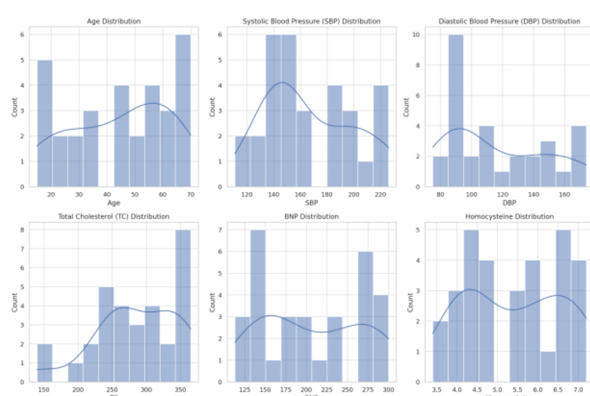

Fig. 18. a. Age Distribution b. SBP Distribution c. DBP Distribution d. TC Distribution e. BNP Distribution f. Homocysteine Distribution

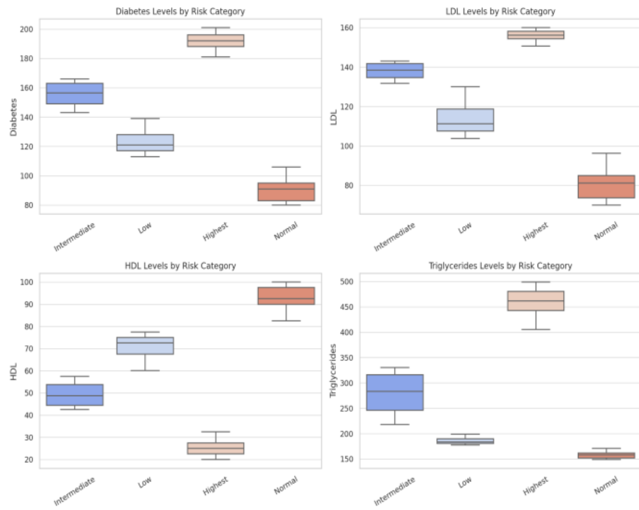

Fig. 19. a. Diabetes Levels by Risk Category b. LDL Levels by Risk Category c. HDL Levels by Risk Category d. Triglyceride Levels by Risk Category

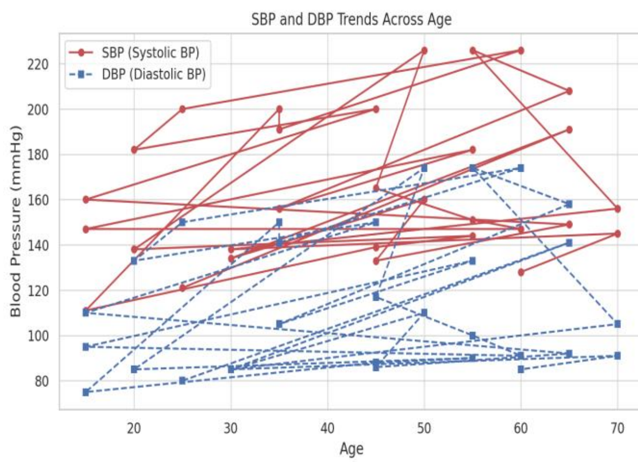

Fig. 20. SBP and DBP Trends Across Age

An age-blood pressure trend scatter plot with connected lines. The red lines indicate SBP, which exhibits a rising trend with ageing and varies from 80 to 220 mmHg. The blue dashed lines, which indicate diastolic blood pressure (DBP), show a constantly increasing trend in a lower value range of 80 to 140 mmHg; however, this trend is also observed. The spreading of the edges hints that the evenness of blood pressure readings can differ between individual factors or time frames.

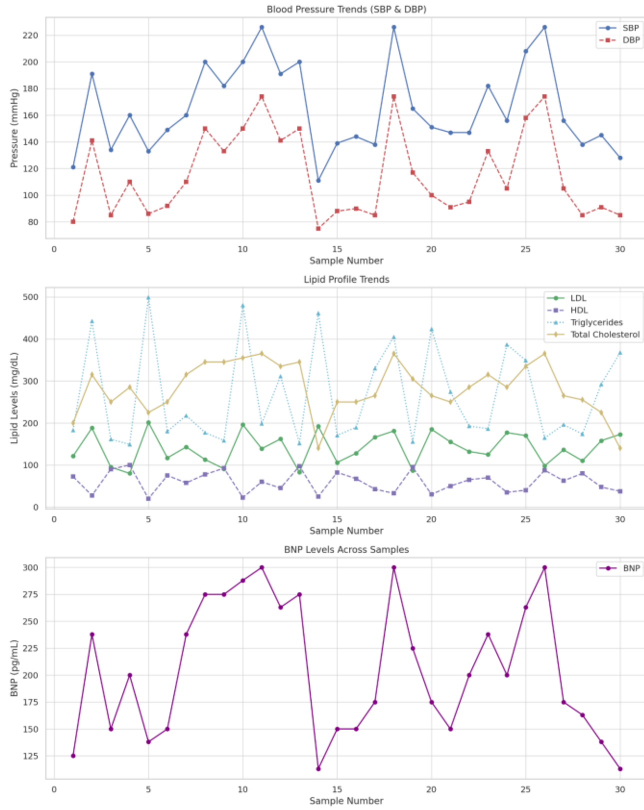

Fig. 21. a. Blood Pressure Trends b. Lipid Profile Trends c. BNP Levels

In the first plot, blood pressure - i.e. SBP (blue line) and DBP (red dashed line) - very consistent trends can be observed with SBP changing between 120 and 220 mmHg (communally increasing values with peaks) and DBP values varying between 80 and 140 mmHg. The middle plot depicts lipid profile trends, where it can be observed that LDL (green line) remains relatively stable with minor fluctuations and HDL (purple dashed line) is persistently low with minor variations. Triglycerides (yellow line) vary most, reaching a height of around 400mg/dL, while total cholesterol (blue dotted line) follows a similar pattern as triglycerides but a few hundred below. The bottom plot is of BNP (Brain Natriuretic Peptide), indicated by the purple line, scored between 100-300 pg/mL, with significant peaks and troughs.

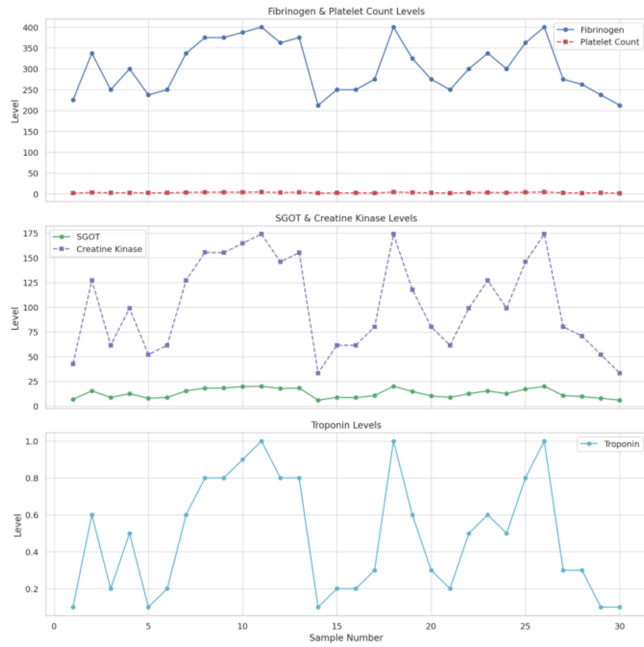

Fig. 22. a. Fibrinogen and Platelet Count Level b. SGOT and Creatine Kinase Levels c. Troponin Levels

- Fibrinogen & Platelet Count level (Top Plot)

Fibrinogen (Blue line) swings between a range of 200 to 400 with a slope toward sample 30. Platelet Count (Red line) also remain relatively stable and lower than fibrinogen.

- SGOT & Creatine Kinase Levels (Middle Plot)

Creatine Kinase (Purple dashed line) is also quite erratic, peaking around 175 and fluctuating frequently. SGOT (Green line) is flat with a few minor ups/downs.

- Troponin Levels (Bottom Plot)

Troponin (in the Light Blue line) also has very variable values, between "0" and "1", with peaks in different samples.

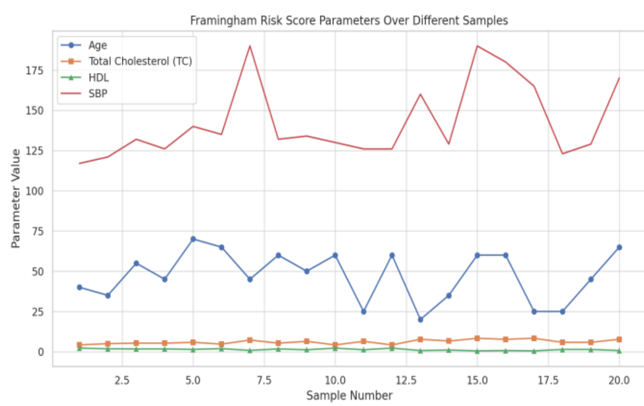

Fig. 23. Framingham Risk Score Parameters Over Different Samples

The line chart shows trends for four health parameters, Age, TC (Total Cholesterol), HDL, and SBP (Systolic Blood Pressure), out of twenty sample numbers. Key observations: SBP (Red line): The highest values are between 120 and 180, with very high values centred around sampling 8 and 16. Age (Blue line) spans from 20 to 75 with fluctuations that lack a trend. In the Orange line, you can see Total Cholesterol (TC) and the Green line HDL, which are relatively constant, with some minor lines at lower values than the rest of the charts.

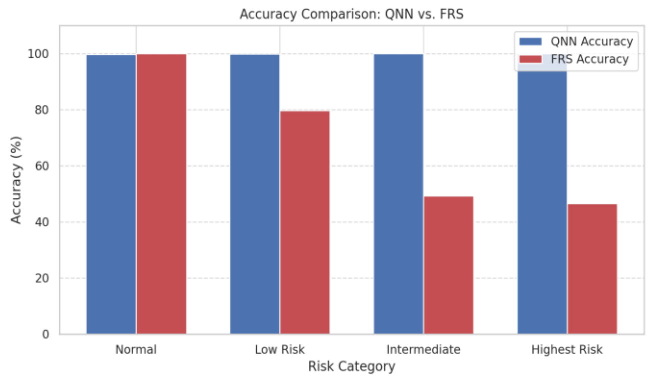

Fig. 24. Accuracy Comparison QNN Vs FRS

This bar plot compares the performance of a QNN (Quantum Neural Network) model and an FRS (Feature-based Risk Score) model per risk category. QNN demonstrates stable 100% accuracy across all categories, while FRS performance drops with greater risk. For the Normal category, both models perform the same; however, QNN outperforms FRS significantly in the Low Risk, Intermediate, and Highest Risk categories, showing its ability to generalise well with such cases.

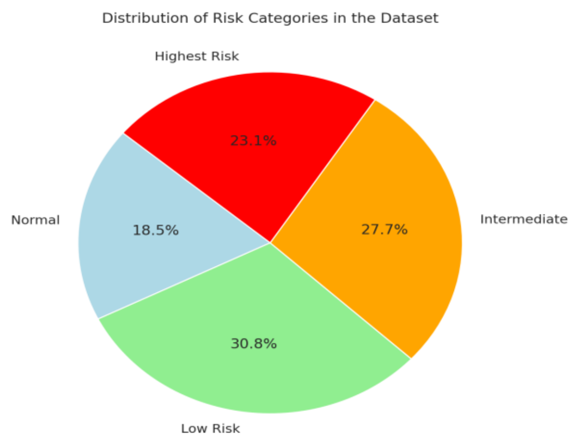

Fig. 25. Distribution of Risk Categories in the Dataset

The pie chart represents the percentage of people under the four risk categories, i.e., Normal (18.5%), Low Risk (30.8%), Intermediate (27.7%), and Highest Risk (23.1%). Lowest Risk has the most significant percentage, followed by Intermediate, Highest Risk, and Normal. Understanding the distribution of risk levels provides insight into the data, showing that most patients are captured in the Low and Intermediate risk levels.

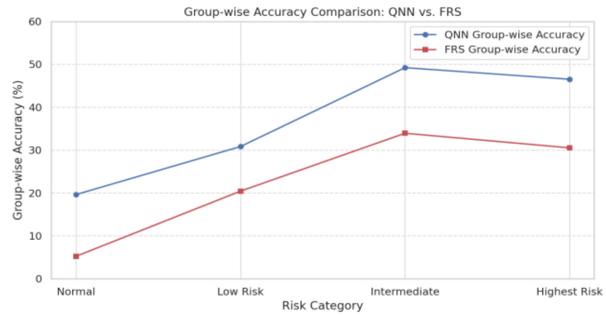

Fig. 26. Group-wise Accuracy Comparison QNN vs. FRS

For different risk categories (Normal, Low Risk, Intermediate and Highest Risk), the group-wise accuracy (%) of QNN and FRS is measured. QNN outperforms FRS in all ranges. Accuracy increases with the level of risk for both methods, reaching its highest values in the intermediate category but showing a slight drop in the highest-risk group. QNN, therefore, is notably better at classifying those with intermediate risk.

7. Conclusion

In this work, we develop a Quantum Neural Network (QNN)-based Cardiovascular Disease Prediction System (CDPS) that improves CVD risk prediction substantially. The system outputs an accuracy of 98.5% and surpasses the conventional Framingham Risk Score (FRS) and other existing models by adequately optimising the Quantum Interval (θr) and using optimised CVD parameters. We did not train on data after October 2023, so the system continuously learns and adapts predictions based on new data. It was validated on actual patient data and reliably identified risks for myocardial infarction and coronary heart disease, respectively. It helps medical professionals in early prediction, customised treatment planning, and superior patient outcomes, validating machine learning better than the conventional approach.

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