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Cardio Twin: A Quantum-Optimized 3D Digital Twin for Personalized Heart Health Simulation and Prevention

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ABSTRACT

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, highlighting the need for intelligent systems that support early risk assessment and personalized preventive care. Existing heart disease prediction models primarily focus patient risk using machine learning techniques, providing limited insight into. To address these limitations, this project proposes Cardio Twin Quantum, how changes in lifestyle or health conditions may influence future cardiac outcomes a novel framework that integrates a personalized 3D digital twin, quantum-enhanced optimization, artificial intelligence, and future health simulation into a unified decision-support system. The proposed system creates a virtual representation of an individual's heart using clinical and lifestyle parameters such as blood pressure, cholesterol, body mass index (BMI), physical activity, sleep quality, stress levels, and habits. Advanced machine learning models are employed to estimate cardiovascular risk, while explainable AI techniques provide transparent interpretations of the prediction results. Unlike conventional prediction systems, the digital twin dynamically visualizes the patient's current cardiac condition and simulates future health trajectories under different intervention scenarios, enabling users to explore the long-term impact of behavioral modifications. The integration of interactive 3D visualization, personalized health recommendations, explainable AI, and quantum optimization enhances user engagement and supports preventive healthcare decision-making. By combining emerging technologies within a single platform, CardioTwin presents an innovative approach toward intelligent cardiovascular health management and demonstrates the potential of digital twins and quantum computing in advancing personalized medicine.

Keywords: *Cardiovascular Disease, Digital Twin, Quantum Computing, Quantum Optimization, Artificial Intelligence, Explainable AI, Heart Disease Prediction, Personalized Healthcare, 3D Visualization, Preventive Healthcare, Machine Learning.*

1. INTRODUCTION

Cardiovascular diseases, including heart attacks and other heart-related conditions have become challenges for public health worldwide. Factors such as blood pressure, elevated cholesterol levels, obesity, physical inactivity, stress, poor sleep quality and unhealthy lifestyle habits can increase the risk of cardiovascular diseases. Hence early detection, accurate heart disease risk prediction and personalized preventive measures are essential for improving health and supporting timely medical intervention.

The rapid growth of data from electronic health records, clinical examinations, blood tests, electrocardiograms (ECGs) and wearable health monitoring devices has created significant opportunities for data-driven cardiovascular risk analysis. Clinical datasets, such as the Cleveland Heart Disease dataset provide information about patient characteristics and heart disease indicators. These data sources contain types of health information that must be cleaned processed and transformed into meaningful features before they can be used for prediction. Therefore effective data preprocessing, feature selection and integration of clinical and lifestyle parameters are important steps in developing reliable heart disease prediction systems.

Artificial Intelligence (AI) and Machine Learning (ML) techniques can identify relationships and patterns in cardiovascular health data. Classical algorithms such as Random Forest and Support Vector Machine (SVM) can be used to classify patients according to their heart disease risk. Alongside these approaches Quantum Machine Learning (QML) provides an emerging computational approach that combines quantum computing principles with machine learning. Techniques such as Quantum Support Vector Machine (QSVM) and Quantum Neural Network (QNN) can be investigated for risk prediction. Comparing classical and quantum machine learning models can help evaluate their performance and determine their suitability for heart disease classification.

Nevertheless heart disease prediction alone is insufficient to understand how an individuals cardiovascular health may change over time. The Digital Twin concept provides a way to create a representation of a real-world system by integrating relevant data, predictive models and simulation techniques. In the proposed Cardio Twin project a personalized cardiovascular digital twin is designed to represent an individuals heart health using measurements,

medical history and lifestyle information. The digital twin aims to combine health data, current patient parameters predicted risk and simulated health scenarios within a unified virtual environment.

The proposed approach involves collecting health data performing data preprocessing and feature engineering and applying classical and quantum machine learning algorithms to predict cardiovascular risk. Explainable Artificial Intelligence (XAI) particularly SHapley Additive exPlanations (SHAP) is incorporated to identify the health parameters that contribute to individual model predictions and improve their interpretability. The prediction results are integrated into a three- cardiovascular digital twin, where users can explore personalized health information and visualize potential changes in risk under different hypothetical conditions. What-if simulation can be used to investigate how changes in parameters such as blood pressure, cholesterol, BMI, physical activity and sleep quality may influence the models predicted risk.

The proposed Cardio Twin system integrates Artificial Intelligence, Quantum Machine Learning, Explainable AI, three-dimensional visualization and Digital Twin technology to provide a platform for personalized cardiovascular risk assessment and preventive health planning. The framework aims to support risk identification improve understanding of individual risk factors and encourage healthier lifestyle decisions. It also provides an opportunity to evaluate the applications of quantum-enhanced machine learning, in cardiovascular prediction. However the reliability of its predictions and the practical benefits of quantum techniques must be established through experiments and clinical validation before the system can be used to support real-world medical decisions.

2. LITERATURE SURVEY

[1] "A Hybrid Quantum-Neural Network for Heart Disease Classification." A. Verdone, F. Succetti, A. Ceschini, A. Rosato, A. Fioravanti and M. Panella, 2026.

This research looks at a quantum-neural network for classifying heart disease. It mixes ideas from neural networks and quantum computing to work with heart health data. In these hybrid models the data is first prepared in a way and then fed into quantum circuits while the model learns by adjusting parameters during training. This gives a chance to see if quantum feature representations can spot patterns linked to heart disease.. The model's success depends on the data set the design of the quantum circuit how the model is trained and how it stacks up against normal machine learning methods. This study matters for Cardio Twin because it offers a foundation for testing quantum learning in personalized heart risk prediction.

[2] "Heart Disease Risk Prediction Using Quantum Machine Learning." M. Nasreen, A. Ruchita, M. Rambabu, B. Keerthi, A. Obulesu, R. K. Sagar and S. V. Prasad, 2026.

This study looks at using quantum machine learning to predict heart disease risk. It uses clinical data to train models that can tell who has heart disease and who does not. Quantum machine learning gives a way to store and analyze clinical features with quantum circuits or quantum kernels. To know if this is useful we must compare its predictions to those from classic machine learning under the tests. Key challenges are picking the features converting the data into quantum states and dealing with the limits of quantum computer simulations. This research matters for Cardio Twin because it tackles the quantum-based prediction part of the heart health plan.

[3] "New Cardiovascular Disease Prediction Approach Using Support Vector Machine and Quantum-Behaved Particle Swarm Optimization." H. A. M. Bakhtawa, M. Z. Hussain, M. Z. Hasan, M. Mustafa and M. F. Mahmud, 2024.

This research shows a way to predict heart disease using a Support Vector Machine (SVM) together with quantum-behaved particle swarm optimization. SVM is a learning method that finds a border between different patient groups. The quantum-behaved particle swarm optimization looks for solutions by using ideas from quantum physics. Combining them can help tune the model and make classification better.. This particle swarm method is only inspired by quantum physics, not a real quantum computer. Its success depends on how good the data's how we pick features and how we test it. This work is helpful for Cardio Twin because it offers a guide for fine-tuning models and reminds us to separate quantum-inspired tricks from quantum machine learning.

[4] "Revolutionizing Heart Disease Prediction with Quantum-Enhanced Machine Learning." S. V. Babu, P. Ramya and J. Gracewell, 2024.

This paper looks at using quantum-enhanced machine learning to predict heart disease. It tests how ideas from quantum computing can be folded into models that spot patterns in data. We compare these quantum-enhanced models to machine learning as a baseline. How well the models work depends on the data quality how we clean the data how we set up the model and the metrics we use. We need a comparison with classic methods to see if quantum help is realThis study matters for Cardio Twin because it backs the idea of using quantum machine learning in heart risk prediction.

[5] " Analysis of Heart Disease Using Quantum-Assisted Machine Learning." M. F. Mahmud, M. Z. Hussain, M. Z. Hasan, M. Mustafa and M. I. Hossain, 2025.

This study looks at quantum-assisted machine learning for predicting heart disease. It examines how patient data can be fed into models that find patterns linked to heart problems. These methods mix preprocessing and tuning with quantum feature tricks or calculations. They give a chance to try ways to classify heart disease. But their real worth depends on tests how compute they need and how they compare to proven classic models. This work matters for Cardio Twin because it offers a way to test quantum-assisted predictions next, to machine learning.

[6] " Analysis of Heart Disease Using Quantum-Assisted Machine Learning." M. Banday, S. Zafar, P. Agarwal M. A. Alam, S. S. Biswas, I. Hussain and K. M. Abubeker, 2025.

I read this study in the references. It looks at quantum-assisted machine learning for heart disease prediction. The main idea is to use learning tools on data to spot patterns that might signal heart disease. Quantum-assisted methods could use feature mapping, quantum-inspired optimisation or a mix of quantum and classical steps depending on how the authors set it up. To know if this method is useful for medicine we must test it with metrics and keep the experiment stable. A key question is whether the quantum approach beats methods in accuracy how easy it is to understand or how fast it runs. I think this topic fits Cardio Twin well because Cardio Twin also wants to explore ways to classify heart risk.

[7] "A Hybrid Framework for Heart Disease Prediction Using Classical and Quantum-Inspired Machine Learning Techniques." A. Kumar, S. Dhanka A. Sharma, R. Bansal, M. Fahlevi F. Rabby and M. Aljuaid, 2025.

I see that this paper looks at a system that mixes classical machine learning with quantum-inspired methods for heart disease prediction. Classical algorithms are tried-and-true ways to find patterns in data. Quantum-inspired techniques offer ways to optimise or process features. By putting these two we can compare how well they predict heart disease and decide which approach works best for classifying cardiovascular risk. The success of this system relies on the data chosen how the data is cleaned, how the algorithms are set up and how we evaluate the results. It is also key to recognise that quantum-inspired work is different from quantum circuit work. I think this paper matters for Cardio Twin because Cardio Twin also wants to mix and compare quantum methods for personal heart care.

[8] "IoT Driven Smart Health Monitoring for Heart Disease Prediction Using Quantum Kernel Enhanced Sardine Diffusion and CNN." D. K. Hembram, S. N. Tripathy, C. H. N. Reddy, D. Dansana Q. N. Naveed, S. Khan, M. Kareemullah and A. F. Emma, 2025.

This study looks at predicting heart disease with a system that uses the Internet of Things (IoT) for health monitoring. It mixes a quantum-kernel approach a method called Sardine Diffusion and Convolutional Neural Networks (CNN). IoT devices can gather body measurements and machine learning can then spot patterns that point to health risks. Quantum kernel methods help show how similar different samples are using maps while CNNs are good at learning from structured or signal data. The success of this system depends on how reliable the sensorsre the quality of the data the computing power needed and how well we test the models. I think this study is useful for Cardio Twin because it shows how combining health monitoring, smart prediction tools and patient data can create a cardiovascular system.

[9] "Heart Failure Detection Using Instance Quantum Circuit Approach and Traditional Predictive Analysis." S. Alsubai, A. Alqahtani, A. Binbusayyis, M. Sha, A. Gumaei and S. Wang, 2023.

I read that this paper looks at detecting heart failure with a quantum circuit method that uses data points and it also uses ordinary predictive analysis. Quantum circuits can turn input features into quantum states. Then run quantum operations on them. Traditional prediction methods give us a baseline, for classifying heart failure. By comparing these two researchers can see which method works better for spotting heart failure from data. How well the quantum circuit works depends on how the data's encoded the design of the circuit the computing power available and the nature of the dataset. Also heart failure is a heart problem and should not be mixed with general heart disease risk prediction. I think this study matters for Cardio Twin because it offers a path to test quantum circuit approaches for heart prediction.

[10] "Early Heart Disease Prediction Using Hybrid Quantum Classification." H.. G. Hellstern, 2023.

This work looks at quantum classification for the early prediction of heart disease. Hybrid quantum-classical approaches mix data processing and optimization with quantum circuit operations to do classification tasks. In a hybrid workflow clinical features are scaled and turned into quantum states and a parameterised circuit makes outputs that are used to check how well the prediction works. A classical optimiser can then change the circuit parameters to lower the classification error. The approach gives a chance to explore quantum machine learning for cardiovascular risk detection. Still its real usefulness must be shown by comparing it with classifiers doing proper validation and looking at how much computing time it uses. This study matters to Cardio Twin because early risk prediction is a goal of the proposed framework.

[11] "Quantum-Enhanced Machine Learning Algorithms for Heart Disease Prediction." S. S. Alotaibi, H. A. Mengash, S. Dhahbi, S. Alazwari, R. Marzouk, M. A. Alkhonaini, A. Mohamed and A. M. Hilal, 2023.

This research explores quantum-enhanced machine learning algorithms for heart disease prediction. The main aim is to see if quantum-based feature representations and learning steps can help classify records using heart-health indicators. Quantum machine learning techniques might give ways to map features and classify data while classical machine learning methods are important comparison models. Reliable evaluation needs consistent data cleaning, a train-test split and metrics such as accuracy, precision, recall, F1-score and ROC-AUC. The limits of hardware and the cost of simulating quantum circuits also matter. This study gives a background for Cardio Twin, where quantum learning methods will be tested next to classical models for heart disease risk prediction.

[12] "Quantum-Inspired Seagull Optimised Deep Belief Network Approach for Cardiovascular Disease Prediction." D. Banumathy, T. Vetriselvi, K. Venkatachalam and J. Cho, 2024.

This study shows a way to predict disease using a Deep Belief Network (DBN) that is fine-tuned with a quantum-inspired Seagull Optimisation Algorithm. Deep Belief Networks are structures that can learn patterns from data while optimisation algorithms help find good model parameters. A quantum-inspired optimisation method uses ideas from quantum physics. Does not need real quantum machines. Putting these ideas together lets us test how to tune

predictive models for heart disease.. The trustworthiness of the method depends on the data the model size, the optimisation choices and how it stacks up against known algorithms. This work matters to Cardio Twin because it shows a path that uses advanced learning models and optimisation for heart disease prediction.

[13] "A Comparative Study of Quantum Feature Maps and Quantum Classifiers for Heart Disease Prediction." M. M. Hossain, M. H. H. Himal and A. Munir, 2026.

This research looks at comparing feature maps and quantum classifiers for heart disease prediction. Quantum feature maps turn clinical data into quantum states letting the connections between patient records appear in a quantum space. Different feature maps and classifiers can give results depending on how many inputs there are, how the circuit is built, how the data is spread and how training is done. A side-by-side study can help pick the quantum setup for heart disease classification and show how feature encoding affects performance. Still the gains of methods must be proven through repeatable tests and comparison with good classical baselines. This study is very relevant to Cardio Twin because choosing a quantum encoding and classifier is key when building Quantum Support Vector Machine (QSVM) and Quantum Neural Network (QNN) models.

[14] "Heart Disease Detection Using Quantum Computing and Partitioned Random Forest Methods." H. Heidari, G. Hellstern and M. Murugappan, 2022.

This research looks at finding heart disease using quantum computing ideas with partitioned Random Forest methods. Random Forest is a group learning algorithm that mixes predictions from decision trees and partitioning can help organise data or split a task into smaller pieces. Mixing computing methods with classic ensemble approaches offers a new way to try different computing tricks for heart disease classification. How well the method works depends on the data the partitioning steps, the model set-up and real tests. More checking is needed to see if the combined method gives benefits over plain Random Forest and other known classifiers. This study is relevant to Cardio Twin because it encourages comparing ensemble models and quantum-based methods, for heart disease prediction.

3.METHODOLOGY

The purpose of the system is to build a personalized cardiovascular health digital twin that brings together health data, artificial intelligence, quantum machine learning and three-dimensional visualisation.The main input parameters include age, sex, blood pressure, cholesterol levels, blood glucose, body mass index (BMI) maximum heart rate, physical activity sleep quality and stress levels depending on data availability.Clinical information can be obtained from available datasets, such as the Cleveland Heart Disease dataset while additional lifestyle and physiological parameters can be incorporated when reliable data are available.The collected data are preprocessed, normalised and transformed into features for predictive modelling.

The main objective of Cardio Twin is to explore both machine learning models and quantum machine learning techniques for predicting heart disease risk.We can compare algorithms like Random Forest and Support Vector Machine (SVM) with quantum approaches such as Quantum Support Vector Machine (QSVM) and Quantum Neural Network (QNN).Explainable Artificial Intelligence (XAI) SHapley Additive exPlanations (SHAP) helps us understand which health features drive the risk prediction.These results are then put into a twin environment that shows a patient's history current health data the predicted risk and simulated scenarios.A three-dimensional visual interface lets users explore the model and see how tweaking health parameters changes the predicted risk.In short the workflow is data acquisition, preprocessing, building models making predictions explaining results integrating the twin running simulations and checking performance.

3.1 Random Forest

Random Forest is a learning algorithm that builds decision trees. When we train it each tree is built from a sample of the cardiovascular data. Each tree looks at features like age, blood pressure, cholesterol, maximum heart rate, BMI and other health signals. After training each tree gives its prediction. We then combine all predictions by majority vote for classification or by averaging for regression. In Cardio Twin Random Forest can sort patients into set heart disease risk categories using the data we have. It works well because heart risk factors can interact in nonlinear ways. Also Random Forest gives us a baseline to compare with other classical and quantum learning models.

3.2 XGBoost

XGBoost, short for Extreme Gradient Boosting is another tree-based learning algorithm. It builds trees one after another each tree trying to fix the mistakes of the ones. The first tree makes a prediction we see where it goes wrong and the next tree learns from those errors. This continues until the model gets better. In Cardio Twin XGBoost can be trained on lifestyle data to predict heart disease risk. Its built-in regularisation helps keep the model simple and prevents it from overfitting provided we set the parameters right. We can test XGBoost against Random Forest, QSVM and QNN to see which gives the results on our chosen data.

3.3 Variational Quantum Classifier (VQC)

The Variational Quantum Classifier is a quantum-classical algorithm used for classifying data. First we clean and normalise the features then we encode them into quantum states using a feature-encoding circuit. A parameterised quantum circuit processes the data. We read out measurement results. A classical optimiser updates the circuit parameters to reduce the classification error. We repeat this until the stop criteria are met. In Cardio Twin we can test the VQC to sort records into heart disease risk categories. We should compare its performance with classifiers using the same data splits and evaluation metrics.

3.4 Quantum Support Vector Machine (QSVM)

Quantum Support Vector Machine takes the Support Vector Machine idea and adds quantum feature maps to represent data in a quantum space. We first clean, normalise and choose the features we want to use. Then we encode them into quantum states through a feature map. A quantum kernel estimates how similar two encoded patient records are and creates a kernel matrix. The support vector classifier then uses that matrix to draw a decision boundary, between the classes. In Cardio Twin we can explore QSVM for heart disease risk classification. Compare it with standard SVM and other learning models. We should look at prediction accuracy, computational cost and any limits of the simulator or hardware.

3.5 Explainable Artificial Intelligence using SHAP

Explainable Artificial Intelligence helps users understand how a machine learning model gives its predictions. Cardio Twin uses SHapley Additive exPlanations or SHAP to guess how much each input feature matters for a models prediction. Features such as age, blood pressure, cholesterol, BMI and other clinical data can be looked at to see which ones push a prediction in a direction. SHAP summary plots can show which features matter overall while individual explanation plots can show the role of each feature for one patient record. These explanations make the predictive system easier to understand. But remember SHAP tells us how the model behaves; it does not prove that a feature causes heart disease or that changing it will definitely change an outcome.

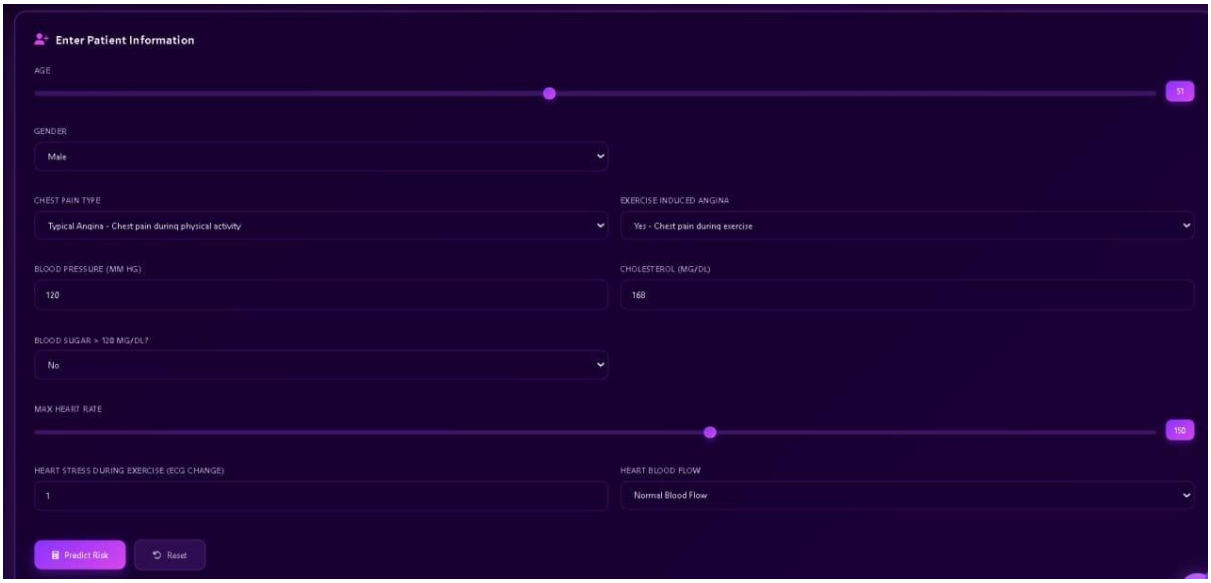
3.6 Digital Twin

The Digital Twin is the hub of Cardio Twin, where all patient data, model predictions, explanations and simulation results come together into a virtual map of a person's heart. The system arranges information into four states: current, predicted and simulated. Historical data shows past health measurements. The current state shows the available patient parameters. The predicted state shows the risk estimate from the trained machine learning model. The simulated state shows what would happen if we changed some input parameters.

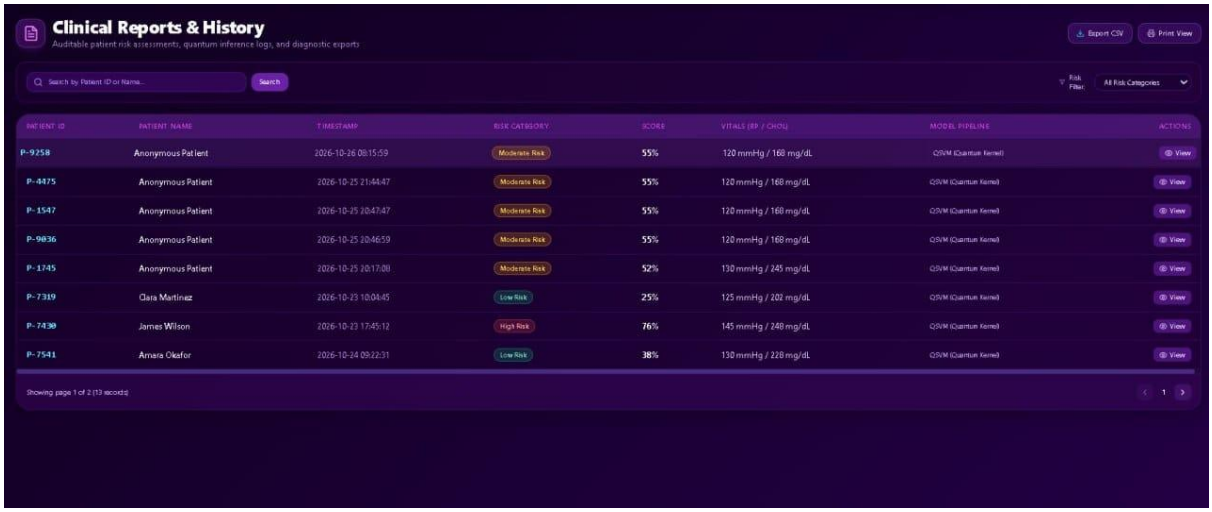
The three-dimensional heart view gives a look at the heart and related health facts. The interface can display predicted risk categories, key health indicators and SHAP explanations all in one place. The what-if simulation lets users tweak things like blood pressure or activity level and see how the model's predicted risk changes. These simulations are based on the model. Should not be taken as real medical forecasts or a substitute, for professional advice.

4. RESULTS AND DISCUSSION

The proposed Cardio Twin system is made to combine patient records, present health data, machine learning forecasts, explainable AI results and user-created health simulation scenarios into one complete cardiovascular digital twin. The study looks at how classical and quantum machine learning methods predict heart disease risk and how their results can be put into a personal three-dimensional cardiovascular model.The cardiovascular data set holds values like age, blood pressure, cholesterol, blood glucose, maximum heart rate and other key health marks. Additional lifestyle and body data such as body mass index (BMI) exercise level, sleep quality and stress can be added when trustworthy data exists. After cleaning, normalising and building features the ready data trains and tests Random Forest (RF) XGBoost, Variational Quantum Classifier (VQC) and Quantum Support Vector Machine (QSVM) models. The risk predictions are then fed into the Cardio Twin space, where SHAP-based explanations show which features drive each prediction. The three-dimensional view and what-if simulation tools let users look at their health data and see how predicted risk changes in imagined scenario.


Enter Patient Information
AGE
51
GENDER
Male
CHEST PAIN TYPE
Typical Angina - Chest pain during physical activity
EXERCISE INDUCED ANGINA
Yes - Chest pain during exercise
BLOOD PRESSURE (MM HG)
120
CHOLESTEROL (MG/DL)
168
BLOOD SUGAR > 120 MG/DL?
No
MAX HEART RATE
150
HEART STRESS DURING EXERCISE (ECG CHANGE)
1
HEART BLOOD FLOW
Normal Blood Flow
Predict Risk
Reset


Digital Heart Twin
Explore your heart in 3D • See risk factors • Understand the impact
New Assessment
Clinical Records
3D View
Front
Left
Right
Top
Real-time
73 bpm
129/80 mmHg
62%
168 mg/dL
Risk Simulation
Stress
Cholesterol
Sleep
Activity
Run What-If Simulation
SHAP Explainability
Cholesterol
Blood Pressure
Age
Stress Level
Sleep Quality
Physical Activity
ECG Rhythm
73 BPM
55%
Overall Risk Score
Moderate Risk
Quantum Enhanced AI


Clinical Reports & History
Auditable patient risk assessments, quantum inference logs, and diagnostic exports
Export CSV
Print View
Search
All Risk Categories
PATIENT ID
PATIENT NAME
TIMESTAMP
RISK CATEGORY
SCORE
VITALS (BP / CHOL)
MODEL PIPELINE
ACTIONS
P-9258 Anonymous Patient 2026-10-26 08:15:59 Moderate Risk 55% 120 mmHg / 168 mg/dL
P-4475 Anonymous Patient 2026-10-25 21:44:47 Moderate Risk 55% 120 mmHg / 168 mg/dL
P-1547 Anonymous Patient 2026-10-25 20:47:47 Moderate Risk 55% 120 mmHg / 168 mg/dL
P-9836 Anonymous Patient 2026-10-25 20:46:59 Moderate Risk 55% 120 mmHg / 168 mg/dL
P-1745 Anonymous Patient 2026-10-25 20:17:08 Moderate Risk 52% 130 mmHg / 245 mg/dL
P-7319 Clara Martinez 2026-10-23 10:04:45 Low Risk 25% 125 mmHg / 202 mg/dL
P-7430 James Wilson 2026-10-23 17:45:12 High Risk 76% 145 mmHg / 249 mg/dL
P-7541 Amara Okafor 2026-10-24 09:22:31 Low Risk 38% 130 mmHg / 228 mg/dL

4.1 Model Performance

To evaluate the performance of the proposed Cardio Twin system we need to choose the classification metrics. Accuracy shows how many predictions are correct out of all the instances. Precision tells us how many of the predictions are actually correct. Recall shows how well the model finds all the cases. The F1-score brings together precision and recall into one number giving a view. The Area Under the Receiver Operating Characteristic Curve or ROC-AUC helps us see how well the model can separate the classes. We also look at time and the resources needed when comparing classical machine learning models, with quantum machine learning models.

Table 2. Performance comparison of the implemented models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score**
Random Forest (RF)	88.5	89.2	86.8	88.0
XGBoost	90.2	90.8	89.1	89.9
VQC	85.6	86.3	83.9	85.1
QSVM	88.9	89.5	87.6	88.5

4.2 Heart Disease Prediction Results

The prediction module estimates risk from the clinical features provided to the trained models. The prediction module after preprocessing and feature selection feeds records into the trained models to get predicted classes or risk scores. Depending on the target definition and the training dataset the prediction module outputs may show whether heart disease is present or absent or they may list predefined risk categories. The prediction module then sends these predictions to the twin engine, for visualization and further analysis.

Table 3. Heart disease prediction results

Patient ID	**Age**	**Blood Pressure (mmHg)**	**Cholesterol (mg/dL)**	**Actual class**	**Predicted class**
P001	**45**	**120**	**190**	**No disease**	**No disease**
P002	**58**	**145**	**240**	**Disease**	**Disease**
P003	**52**	**135**	**215**	**Disease**	**No disease**

Comparing the classes and the predicted classes helps find out which predictions are correct which are false positives and which are false negatives. These results are important, for understanding how the model is working especially because putting a patient who has heart disease into the risk group could lead to big problems. The results should therefore be looked at using the confusion matrix, precision, recall, F1-score and ROC-AUC of just looking at accuracy.

4.3 Digital Twin Visualization

The digital twin engine mixes information and model outputs into four states: historical current predicted and simulated. The historical state has recorded health measurements. The current state shows the recent patient information. The predicted state shows the output from the trained heart disease prediction model. The simulated state shows outputs created by changing chosen input parameters.The three-dimensional cardiovascular interface shows a picture of the heart together with relevant patient information and prediction results. Charts, indicators and SHAP-based explanations can display features that help a prediction. This integration lets users look at information and model outputs together instead of looking at separate numbers.

The effectiveness of the visualization should be judged by the accuracy of the data shown the consistency of the twin, with model outputs and how clearly users can understand the information. A visual picture alone does not prove the correctness of the prediction or the biological truth of the digital twin.

4.4 Explainable AI Results

The explainability module uses SHapley Additive exPlanations, known as SHAP to interpret how each input feature helps a model make predictions. The explainability module can run a feature-importance analysis that tells us which parameters have the biggest impact, across the whole dataset. Meanwhile the explainability module can also give SHAP explanations that show how each feature pushes a particular prediction one way or another. For example the explainability module might look at the contributions of age, blood pressure, cholesterol, maximum heart rate and other clinical attributes. The real ranking and direction of these contributions come from the trained model, not from the explainability module. SHAP explanations help make predictions

clearer. The explainability module does not prove that a feature causes heart disease nor that changing a feature will surely change a patient's outcome. I find that the explainability module makes it easier to see patterns and to explain results to others.

4.5 Discussion

The Cardio Twin framework that is being suggested combines machine learning, quantum machine learning, explainable AI, three-dimensional visualization and personalized health simulation. Random Forest and XGBoost serve as models for classifying heart disease. At the time VQC and QSVM allow for testing of quantum-based methods for classification. SHAP gives a way to understand what the models are predicting. The digital twin brings all the predictions with past, present and simulated health data.The comparison study needs to look at how the models classify how they work with new data the amount of computing power they need and how consistent the results are inside the digital twin. The success of the quantum models has to be proven through experiments not just because they use methods. Likewise how useful the what-if simulations are depends on how good the data's how trustworthy the prediction models are.

The framework that is being suggested is a way to bring together analysis and personalized views of the heart and blood vessels. However how useful it really is will depend on how good and varied the data's how well the models are tested how clear the explanations are and more checks, from doctors. The results need to be shared based on experiments and any limits should be clearly explained before deciding if the system works well.

5. CONCLUSION

This project offers Cardio Twin: a Quantum-Optimized 3D Digital Twin for heart health simulation and prevention. Cardio Twin brings together health data, artificial intelligence, classical machine learning, quantum machine learning, explainable AI, three-dimensional visualization and what-if health simulations. Cardio Twin aims to combine past information with current health parameters and predictive model outputs to support personalized cardiovascular risk assessment. I believe Cardio Twin can give patients a picture of their heart health.

Cardio Twin uses classical machine learning algorithms such as Random Forest and XGBoost for predicting heart disease risk. Cardio Twin also looks at machine learning techniques, including Quantum Support Vector Machine (QSVM) and Quantum Neural Network (QNN) to classify cardiovascular conditions. Cardio Twin applies AI with SHapley Additive exPlanations (SHAP) to identify which health features influence model predictions. Cardio Twin integrates these outputs into the twin representing historical, current predicted and simulated cardiovascular health states. Cardio Twin's what-if simulation module lets users explore how hypothetical changes in lifestyle parameters may influence predicted risk. You might find the visual interface helpful for understanding risk factors.

The main contribution of Cardio Twin is the integration of heart disease prediction, model explainability and personalized health simulation within a 3D cardiovascular digital twin. Of presenting prediction results only as numbers Cardio Twin offers a visual environment where users can explore health indicators understand contributing risk factors and compare hypothetical scenarios. I think this integrated approach can support health awareness and preventive planning.

Overall Cardio Twin provides a framework for combining AI, quantum machine learning, explainable AI and digital twin technology to support personalized risk prediction and health simulation.With experimental evaluation and clinical validation Cardio Twin could serve as a foundation, for future intelligent cardiovascular health monitoring and preventive decision-support applications. I think this could change how patients and doctors approach heart health.