Heart Disease Predictor Using QNN

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***Abstract*—Heart disease remains one of the leading causes of death worldwide, with early detection being crucial for effective treatment and prevention. This study presents a Quantum Neural Network (QNN)-based approach for predicting the likelihood of heart disease using patient medical data. The proposed hybrid model combines classical preprocessing with a quantum variational circuit layer to exploit the representational advantages of quantum computation. The model processes input features such as age, sex, blood pressure, cholesterol levels, and other key clinical indicators to generate a probability score indicating the risk of heart disease. By leveraging quantum-enhanced transformations and non-linear feature mappings, the QNN effectively captures complex correlations in the data that traditional machine learning methods might overlook. Evaluation results demonstrate that the proposed model achieves an accuracy of 82.88%, an F1-score of 0.848, and an AUC score of 0.88, indicating balanced classification performance. This approach has the potential to contribute to early diagnosis, enabling timely medical interventions and reducing mortality rates.**

***Index Terms*—Quantum Neural Network, Heart Disease Prediction, Quantum Computing, Hybrid Model, Machine Learning**

I. Introduction

Cardiovascular diseases (CVDs), particularly heart disease, account for millions of deaths annually, representing a significant global health concern. According to the World Health Organization, nearly 17.9 million people die each year from CVDs [1], [2], highlighting the urgent need for improved diagnostic methods. Traditional diagnostic processes often rely on manual interpretation of patient data, which can be time- consuming and prone to human error. The rapid growth of healthcare data and advancements in computational techniques, including deep learning [3], [4] and quantum machine learning [5]–[7], offer new possibilities for more accurate and efficient medical diagnosis.

Classical machine learning methods such as logistic regression [8], support vector machines [9], and multilayer perceptrons (MLPs) [3], [10] have been employed with varying success but often require feature engineering or can overfit on small datasets. Recent advancements in quantum computing propose Quantum Neural Networks (QNNs) as a novel approach to handle high-dimensional data by exploiting quantum properties such as superposition and entanglement [5], [6]. QNNs encode classical inputs into quantum states and employ parameterized quantum circuits as trainable models, potentially enhancing representation power and generalization.

In this study, we propose a hybrid classical-quantum heart disease prediction model integrating a QNN layer within a deep learning framework. Our model leverages the Kaggle "Heart Disease Prediction" dataset [11] and is designed to provide accurate, computationally efficient diagnoses to assist healthcare professionals in timely decision making. The remainder of the paper is structured as follows: Section II reviews related work, Section III presents existing work with classical models, Section IV details the methodology, Section V presents experimental results, Section VI discusses findings, and Section VII concludes with future directions.

II. Related Work

Heart disease prediction has been extensively studied through classical machine learning approaches. For instance, logistic regression [8], support vector machines [9], [12], decision trees, and neural networks including perceptrons [10] and MLPs have been employed with varying success. Hybrid models such as ensemble and feature-engineered methods have also been explored [13]–[16].

Quantum machine learning introduces novel models leveraging superposition and entanglement [5], [6]. Recent work demonstrates QNN applications to diagnosis [7] and causal machine learning in healthcare [17]. Radiology applications of ML also highlight its clinical value [18], [19].

III. Existing Work

Several machine learning models have been applied to heart disease prediction. Logistic Regression achieved an accuracy of around 81% [14], while Decision Trees performed slightly lower at 79% [15]. Multilayer Perceptrons (MLPs) demonstrated improved performance with accuracies near 83% [13]. Support Vector Machines (SVMs) combined with ANN reached comparable results [12]. However, these models either lacked robustness to nonlinear feature interactions or required heavy preprocessing. The proposed QNN-based hybrid model differs by incorporating a variational quantum circuit layer, enabling enhanced representation of feature correlations. Our results show that QNN achieved an accuracy of 82.88% and F1-score of 0.848, outperforming some classical baselines while offering quantum-enhanced generalization.

IV. Methodology

A. Dataset

The dataset comprises records from Kaggle [11] and UCI Repository [20].Each includes 12 clinical features alongside a binary heart disease label indicating presence (1) or absence (0).

TABLE I
CLINICAL FEATURES IN THE KAGGLE HEART DISEASE DATASET

Column	Description
Age	Age of the patient [years]
Sex	Sex of the patient [M: Male, F: Female]
ChestPainType	Chest pain type [TA, ATA, NAP, ASY]
RestingBP	Resting blood pressure [mm Hg]
Cholesterol	Serum cholesterol [mg/dl]
FastingBS	Fasting blood sugar [1 if ¿120 mg/dl, else 0]
RestingECG	Resting ECG results [Normal, ST, LVH]
MaxHR	Maximum heart rate achieved
ExerciseAngina	Exercise-induced angina [Y/N]
Oldpeak	ST depression (numeric)
ST_Slope	Slope of ST segment [Up, Flat, Down]
HeartDisease	Output class [1: heart disease, 0: normal]

B. Data Preprocessing

Categorical variables were encoded using *scikit-learn*'s LabelEncoder to transform discrete categories into numerical form suitable for model training. Continuous numerical features such as age, cholesterol, and blood pressure were standardized using the *StandardScaler*, ensuring zero mean and unit variance for stable gradient updates. To preserve the class balance, a stratified 70%-30% train-test split was applied, which maintained the ratio of positive to negative cases in both subsets.

C. Quantum Neural Network Architecture

The hybrid architecture (Figure 1) combines dense layers with a variational quantum circuit [5], [6]. Such integration allows leveraging entanglement for non-linear feature mapping.

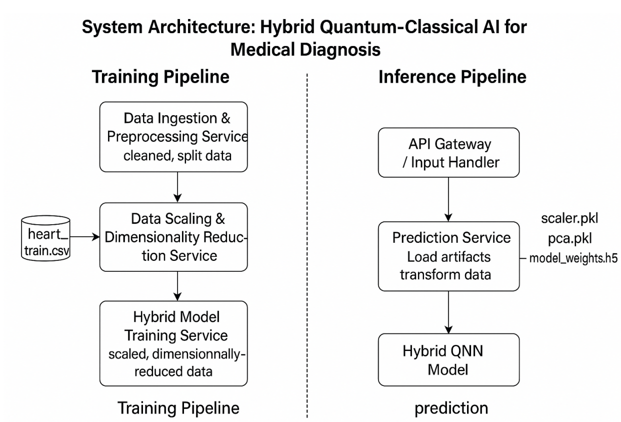

Fig. 1. Hybrid Classical-Quantum Neural Network Architecture.

Architecture Details:

- **Input:** Preprocessed 8-dimensional feature vector representing patient attributes.
- **Classical Dense Layers:** Two fully connected layers with 32 and 8 neurons respectively, each employing the ReLU activation function to capture nonlinear feature interactions.
- **Quantum Layer:** An 8-qubit, 2-layer variational quantum circuit built using parameterized single-qubit rotation gates (R_x, R_y, R_z) combined with controlled entangling gates (CNOT). The quantum layer projects classical features into a higher-dimensional Hilbert space, enabling richer feature transformations through quantum superposition and entanglement. Trainable rotation angles act as learnable parameters, optimized during backpropagation.
- **Post-Quantum Dense Layer:** A 16-neuron fully connected layer with ReLU activation followed by dropout (rate = 0.3) to reduce overfitting by randomly deactivating neurons during training.
- **Output:** A single neuron with sigmoid activation, providing a probability score for binary classification (heart disease present vs absent).

This hybrid design allows the quantum variational circuit to enhance classical learning by modeling complex correlations between features, which traditional neural networks might fail to capture efficiently.

D. Training and Optimization

The model was trained using the binary cross-entropy loss function, suitable for binary classification tasks. The *Adam optimizer* was employed with a learning rate of 5×10^{-4} to ensure efficient and adaptive gradient updates.

To avoid overfitting, an early stopping criterion monitored validation loss and halted training when no improvement was observed over five consecutive epochs. The network was trained with a mini-batch size of 16 for up to 30 epochs, balancing computational efficiency with learning stability. Dropout layers in the dense blocks further improved generalization.

The quantum layer was simulated using the *PennyLane* and *Qiskit* frameworks on classical CPUs. During training, gradients from the quantum layer were computed using the parameter-shift rule, enabling seamless integration with backpropagation. This hybrid optimization process allowed the model to learn effective representations by combining classical gradient descent with quantum variational circuit tuning.

V. EXPERIMENTAL RESULTS

A. Performance Comparison

Table II compares the proposed hybrid quantum model with classical baselines. The evaluation is based on three key metrics: Accuracy, F1-Score, and Area Under the ROC Curve (AUC).

TABLE II
PERFORMANCE COMPARISON OF QNN AND CLASSICAL BASELINES

Model	Accuracy	F1-Score	AUC
Logistic Regression	0.81	0.82	0.84
Decision Tree	0.79	0.80	0.82
Multilayer Perceptron (MLP)	0.83	0.84	0.86
Quantum Hybrid (QNN)	0.8288	0.848	0.88

B. Interpretation of Metrics

Accuracy measures the proportion of correctly classified cases (both positive and negative) out of the total samples. While useful for an overall view, it may be misleading in imbalanced datasets. For instance, a model predicting all patients as "No Heart Disease" could still achieve high accuracy if negatives dominate the dataset.

F1-Score is the harmonic mean of precision and recall, providing a balanced measure of the model's ability to detect both positive (heart disease) and negative (no disease) cases. The QNN achieves an F1-score of 0.848, which highlights its balanced classification capability. This is especially critical in medical applications where both false negatives (missed diagnosis) and false positives (unnecessary alarms) carry serious consequences.

AUC (Area Under the ROC Curve) evaluates the model's ability to distinguish between classes at various threshold settings. An AUC closer to 1 indicates strong discriminative power. The QNN's AUC of 0.88 suggests that it maintains superior sensitivity-specificity trade-offs compared to classical models.

C. Confusion Matrix

Table III shows the confusion matrix for the proposed QNN model, indicating its performance in correctly identifying patients with and without heart disease.

TABLE III
CONFUSION MATRIX OF QNN MODEL

	Predicted No	Predicted Yes
Actual No	39	11
Actual Yes	8	53

D. ROC Curve

The ROC curves (Figure 2) compare the QNN against classical baselines, illustrating superior sensitivity-specificity balance.

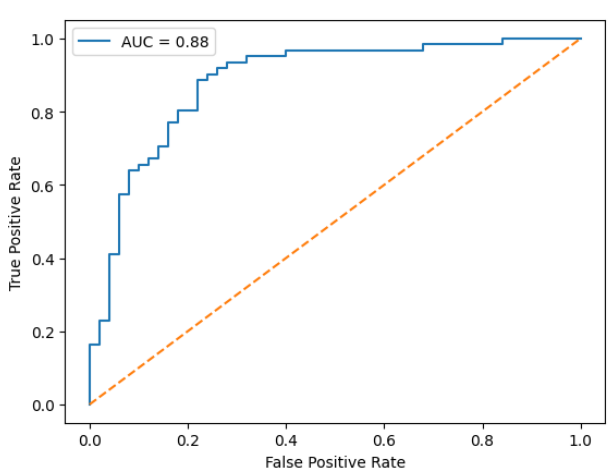

Fig. 2. ROC curves for quantum hybrid and classical models.

VI. Discussion

Our results demonstrate that QNN provides competitive accuracy compared to classical models while achieving stronger F1 and AUC values. The key improvement lies in the ability of quantum circuits to model complex correlations without requiring manual feature engineering. Limitations include dependency on quantum hardware simulators and limited scalability for very large datasets. These results align with prior findings in medical AI [17], [19], showing potential of quantum-enhanced models for diagnostic support. Similar advances are seen in cardiology imaging [18] and large-scale heart disease studies [2].

VII. Conclusion

This study demonstrates that a hybrid deep learning model with QNN can effectively predict heart disease with 82.88% accuracy and an F1-score of 0.848. Such models can serve as supplementary tools for early diagnosis, enabling healthcare professionals to prioritize high-risk patients. Future work may focus on integrating lifestyle and genetic features, and exploring explainable AI techniques to improve clinical trust.

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