Minimax Theory and its Applications

Volume 11 (2026), No. 2s, 887 to 906

Variational Quantum Classifier with Hybrid Quantum-Classical Learning for Intelligent Cardiovascular Risk Screening

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Abstract
Cardiovascular risk classification requires dependable interpretation of interconnected clinical, metabolic, and lifestyle indicators within preventive healthcare analytics. Conventional learning approaches often face difficulty in preserving nonlinear dependencies across heterogeneous cardiovascular attributes. The proposed Variational Quantum Classifier with Hybrid Quantum-Classical Learning (VQC-HQCL) framework addresses such complexity through a structured quantum-assisted classification pathway. Clinical cardiovascular records undergo harmonisation and stratified partitioning to maintain stable, balanced learning conditions. Quantum feature encoding transforms prepared attributes into circuit-compatible states, enabling interaction-aware representation within a variational quantum architecture. The Variational Quantum Classifier functions as the predictive learning core, capturing discriminative cardiovascular patterns through parameterised circuit operations. Hybrid Quantum-Classical Learning supports iterative refinement by combining quantum state processing with classical parameter optimisation. Final classification assigns cardiovascular risk status for screening-oriented decision support in structured clinical practice. The framework contributes a medically grounded, computationally feasible approach for nonlinear cardiovascular relationship modelling and intelligent risk assessment under current quantum learning constraints.

Keywords: Cardiovascular Risk Classification - Variational Quantum Classifier - Hybrid Quantum-Classical Learning - Quantum Feature Encoding - Intelligent Healthcare Analytics.

1. Introduction

Health remains one of the most valuable foundations of human well-being, directly influencing quality of life, productivity, and long-term physiological stability. Healthcare systems continuously seek reliable strategies capable of supporting early identification of disease vulnerability, reducing preventable complications, and strengthening clinical decision-making. Increasing lifestyle irregularities, metabolic imbalance, reduced physical activity, dietary changes, and prolonged physiological stress have substantially intensified the burden of chronic disorders, particularly cardiovascular abnormalities[1]. Such growing clinical pressure has strengthened the need for intelligent healthcare frameworks capable of recognizing disease-associated physiological patterns before severe cardiovascular deterioration emerges.

Cardiovascular diseases represent a major healthcare concern because structural and functional abnormalities within the circulatory system frequently progress through accumulated physiological burden rather than sudden clinical manifestation[2]. Blood pressure irregularities, cholesterol imbalance, glucose dysregulation, obesity, smoking behavior, alcohol exposure, and physical inactivity collectively influence cardiovascular vulnerability through interconnected physiological pathways. Reliable cardiovascular assessment therefore depends upon multidimensional interpretation rather than isolated examination of individual medical indicators. Traditional clinical assessment alone often becomes insufficient when subtle nonlinear dependencies remain hidden within complex cardiovascular observations[3].

Cardiovascular risk prediction consequently serves an important role in preventive healthcare because timely recognition of disease susceptibility supports early clinical intervention, improved treatment prioritization, and strengthened patient monitoring[4]. Reliable prediction frameworks assist healthcare professionals in identifying physiologically vulnerable populations before progression toward severe cardiovascular complications. Effective risk prediction additionally reduces diagnostic uncertainty by supporting data-driven cardiovascular

evaluation capable of capturing multidimensional physiological relationships associated with disease emergence[5].

Conventional machine learning approaches have substantially improved predictive healthcare analytics through pattern recognition and computational learning. Cardiovascular information frequently contains intricate physiological interactions that remain difficult to model using traditional computational assumptions[6]. Hidden nonlinear relationships among hemodynamic, metabolic, demographic, and behavioral indicators may limit predictive consistency, particularly when disease boundaries exhibit multidimensional complexity. Such limitations create a growing need for advanced learning structures capable of strengthening cardiovascular representation while preserving computational feasibility[7].

The proposed VQC-HQCL framework addresses such challenges through integration of Variational Quantum Learning (VQC) and Hybrid Quantum Optimization (HQCL) for cardiovascular risk classification. Within this framework, Clinical Data Acquisition captures multidimensional cardiovascular indicators required for meaningful disease understanding. Clinical Data Harmonization establishes statistically stable and physiologically consistent cardiovascular representation[8]. Stratified Data Partitioning preserves balanced disease exposure during learning and evaluation. Quantum Feature Encoding transforms harmonized cardiovascular information into quantum-compatible representations suitable for nonlinear interaction learning[9].

The Variational Quantum Classifier (VQC) functions as the predictive learning component responsible for discovering hidden cardiovascular patterns through parameterized quantum transformations. Such learning supports improved representation of complex cardiovascular interactions that frequently remain difficult to distinguish through conventional computational structures. Hybrid Quantum Optimization (HQCL) strengthens predictive refinement by integrating quantum learning behavior with classical optimization mechanisms, enabling stable parameter adjustment under practical computational limitations. Cardiovascular Risk Classification subsequently converts learned cardiovascular relationships into clinically interpretable disease predictions suitable for healthcare screening.

The novelty of the proposed work lies in the development of a cardiovascular-aware VQC-HQCL framework capable of integrating harmonized physiological representation, quantum feature transformation, variational cardiovascular learning, and hybrid optimization to strengthen nonlinear cardiovascular interaction modeling for reliable cardiovascular risk classification.

1.1. Problem Statement

Cardiovascular disease prediction requires reliable interpretation of multidimensional clinical indicators, including blood pressure, cholesterol, glucose, body composition, and lifestyle-related factors. These indicators often interact through nonlinear physiological relationships, making accurate risk classification challenging for conventional computational models. Traditional statistical approaches depend on simplified assumptions and may fail to represent hidden dependencies among cardiovascular variables. Classical machine learning methods improve prediction capability, yet performance may be limited when clinical features contain complex interaction patterns, class imbalance, and overlapping risk boundaries. In cardiovascular screening, misclassification of vulnerable patients can delay preventive care and reduce the effectiveness of clinical decision support. Therefore, a technically stronger learning framework is required to improve cardiovascular risk classification through meaningful representation of physiological, metabolic, and behavioral factors. The proposed VQC-HQCL framework addresses this problem by integrating quantum feature encoding, variational quantum learning, and hybrid quantum-classical optimization to capture nonlinear cardiovascular relationships and support reliable classification of cardiovascular disease presence or absence.

1.2. Motivation an Objective

Cardiovascular diseases continue to impose substantial clinical and social burden through progressive vascular dysfunction, metabolic imbalance, and lifestyle-associated risk exposure. Effective cardiovascular risk classification supports preventive screening by enabling timely recognition of vulnerable records from routine health observations. Structured cardiovascular data contains meaningful information related to age, body composition, blood pressure, cholesterol, glucose status, smoking, alcohol intake, and physical activity; however, nonlinear interaction among such attributes can restrict predictive consistency in conventional learning environments. The motivation for the proposed work arises from the requirement for an interaction-sensitive, computationally feasible framework capable of preserving complex cardiovascular relationships during classification. The objective focuses on developing a Variational Quantum Classifier with Hybrid Quantum-

Classical Learning for cardiovascular risk classification. Clinical data harmonisation and stratified partitioning establish stable learning conditions, while quantum feature encoding transforms cardiovascular attributes into circuit-compatible representations. Variational quantum learning captures discriminative patterns through parameterised quantum transformations, and hybrid quantum-classical optimisation refines circuit parameters through coordinated classical correction. The proposed framework aims to strengthen risk-sensitive classification, support reliable screening-oriented decision assistance, and establish a medically grounded quantum-assisted approach for intelligent cardiovascular analytics.

2. Literature Review

MBLSTM-Cloud [10] designed a mobile-cloud cardiovascular prediction pipeline centred on a modified bidirectional long short-term memory network and supervised learning models subjected to hyperparameter tuning. The cloud environment supports remote collection, transmission, and computational processing of clinical attributes gathered through mobile healthcare access.PTDNN-PCA [11] structured heart disease prediction through a transfer-based feature extraction strategy. A pre-trained deep neural network is employed to obtain discriminative representations from the available cardiac input data, reducing dependence on manually designed feature engineering. Principal component analysis is subsequently applied to compress the extracted feature space and retain informative variation while removing redundancy.GWHHO-ShCNN[12] developed a distributed heart disease detection framework using Spark architecture and an optimization-assisted Shepard convolutional neural network. Slave nodes undertake preprocessing and feature-fusion operations, including missing-value handling and normalisation, while the master node performs disease classification. The classifier is supported by a combined Grey Wolf Optimizer and Horse Herd Optimization mechanism, which guides parameter configuration for the Shepard convolutional network.

FGRU-PPG [13] formulated a non-invasive therapy prediction method from photoplethysmography signals collected from ischemic heart disease patients. Signal characteristics are extracted through the Gabor–Wigner transform using statistical identities. The extracted representation enters a fuzzy gated recurrent unit network comprising GRU and bidirectional GRU layers with fuzzy processing components.FL-GNN [14] proposed a privacy-preserving federated learning architecture for heart attack risk prediction using graph neural networks. Preprocessed healthcare records are transformed into graph-structured representations distributed across three clients, allowing patient data to remain local. Each client trains a graph neural network to model relationships among clinical features, transmitting only learned parameters rather than raw records.Transformer-HD [15] introduced an early heart disease detection and classification tool founded on transformer mechanisms. The methodological design uses an encoder-oriented attention architecture to learn interrelationships among clinical indicators without relying exclusively on sequential recurrence or local convolution. Self-attention supports feature-to-feature contextual weighting, allowing clinically relevant dependencies to be captured during representation learning.

HAAP-CNN [16]. constructed an Internet of Things and cloud-based healthcare monitoring framework for heart disease detection using a hierarchical auto-associative polynomial convolutional neural network. Cardiac-related information is collected through connected sensors and forwarded for cloud-supported analysis. Shape-Aware Mesh Normal Filtering is applied during preprocessing to suppress noise and enhance input quality. AEM [17] developed an interpretable multi-task and multi-modal cardiac disease prediction framework combining three-dimensional cardiac anatomy with electrocardiographic information. The method uses an attention-based fusion mechanism to relate structural imaging characteristics with electrical cardiac signals.HQNN [8] proposed a hybrid quantum-neural network for cardiovascular disease classification using the Cleveland heart disease dataset. Classical autoencoders first compress the original clinical feature space into a reduced latent representation suitable for quantum processing. The compressed variables are then supplied to a quantum neural network founded on variational quantum computation for binary classification.

FQML [18] introduced a fuzzy quantum machine learning logic framework for optimised disease prediction. The method combines fuzzy reasoning, which represents uncertain or imprecise clinical information through graded membership, with quantum machine learning operations intended to model complex decision boundaries. AI-QML [19] presented an artificial intelligence-driven quantum machine learning framework for predictive healthcare analytics. The methodological orientation combines classical artificial intelligence procedures for medical-data preparation and predictive learning with quantum machine learning components designed for healthcare pattern analysis.BM-TCIA-QSANN [20] proposed an Internet of Things-supported biomedical tongue colour image analysis framework using an optimised quantum self-attention neural network. Tongue images and type 2 diabetes mellitus tongue-image data form the visual inputs. Maximum Correntropy Quaternion Kalman Filtering is applied to remove noise and enhance colour-image quality before representation learning.

DQVeriChain[21] proposed a distributed criminal-tracking architecture combining quantum-state verification, decentralised identifiers, a self-attentive large language model, and blockchain storage. The methodological pipeline is organised around identity-secured information exchange, blockchain-supported record integrity, and verification of quantum-associated states before analytical processing. QGA-AF [22] designed an atrial fibrillation detection framework based on electrocardiogram signals and quantum genetic ensemble optimisation. Electrocardiogram recordings are segmented using overlapping sliding windows and filtered within a defined frequency band for noise reduction. Time-domain and frequency-domain features are extracted alongside automated representations learned through a one-dimensional convolutional neural network and bidirectional long short-term memory architecture.QENNA [23] introduced a quantum-enhanced neural network architecture for early Alzheimer's disease detection from magnetic resonance imaging. The framework integrates quantum convolutional processing with classical deep learning to extract disease-related representations from brain images. Data diversity is strengthened through quantum-oriented augmentation mechanisms involving quantum generative adversarial networks and quantum walks.

Q-DCNN [24] designed an uncertainty-aware classical–quantum dual-channel neural network for heart disease detection. The classical branch employs bidirectional long short-term memory processing with Kolmogorov–Arnold Network layers, while the quantum branch combines dense Kolmogorov–Arnold processing with parameterised quantum circuits. Clinical data undergo missing-value handling, categorical encoding, scaling, outlier management, and imbalance correction before training. QHF-CS [25] proposed a quantum-enhanced heart failure prediction framework using a quantum convolutional neural network with metaheuristic feature-qubit selection. Skewed and heterogeneous clinical variables are examined through optimisation procedures involving Cuckoo Search Optimization, Artificial Bee Colony, and Particle Swarm Optimization, with selected features encoded as quantum states. The quantum circuit architecture incorporates feature maps and parameterised ansatz structures, including ZZFeatureMap, RealAmplitudes, and EfficientSU2.

3. Variational Quantum Classifier with Hybrid Quantum-Classical Learning

Variational Quantum Classifier with Hybrid Quantum-Classical Learning for Cardiovascular Risk Classification (VQC-HQCL) is a hybrid quantum learning framework that encodes harmonized clinical attributes into quantum states and learns cardiovascular risk patterns through parameterized quantum circuits. The approach combines variational quantum learning with classical optimization to capture nonlinear interactions among physiological, metabolic, and lifestyle factors, supporting reliable classification of cardiovascular risk presence or absence through adaptive quantum decision boundaries.

3.1. Clinical Data Acquisition

Clinical Data Acquisition establishes the foundational clinical structure required for cardiovascular risk classification. Reliable cardiovascular screening depends strongly on the quality, diversity, and physiological relevance of collected medical attributes. Since cardiovascular abnormalities emerge through complex interactions among metabolic, demographic, and behavioral variables, careful acquisition of clinically meaningful observations becomes essential for stable learning in downstream quantum-assisted prediction. Structured cardiovascular records therefore form the basis through which medically interpretable feature representation is achieved.

The acquisition process begins with the systematic retrieval of clinically validated patient attributes associated with cardiovascular health status. The selected dataset contains multidimensional medical observations describing physiological condition, demographic variability, and lifestyle behavior. Let the cardiovascular clinical profile be represented as:

$$C = \{x_1, x_2, x_3, \ldots, x_n\} \tag{1}$$

where Cdenotes the complete cardiovascular feature space and $x_n$represents an individual clinical variable contributing to cardiovascular assessment. Within the present framework, ncorresponds to clinically relevant variables including age, body composition, blood pressure, cholesterol concentration, glucose level, smoking status, alcohol intake, and physical activity.

Physiological indicators demand particular attention because cardiovascular instability often develops through accumulated biological stress rather than isolated disturbances. Blood pressure serves as an important cardiovascular marker because persistent vascular strain directly influences arterial integrity and cardiac workload. Systolic and diastolic blood pressure values are mathematically represented as:

$$\mathrm{BP} = \frac{\mathrm{SBP} + \mathrm{DBP}}{2} \tag{2}$$

where SBPdenotes systolic blood pressure and DBPindicates diastolic blood pressure. Such measurements provide valuable physiological signals reflecting hemodynamic regulation, vascular stiffness, and circulatory adaptation.

Body composition variables also contribute substantially to cardiovascular screening. Excess body mass frequently correlates with hypertension, metabolic imbalance, and impaired cardiovascular efficiency. Body Mass Index provides a standardized estimate of body composition and is computed as:

$$BMI = \frac{W}{H^2} \tag{3}$$

where Wdenotes body weight measured in kilograms and Hrepresents height in meters. Elevated body mass frequently increases cardiovascular strain through altered metabolic regulation and inflammatory burden, making body composition an essential acquisition component.

Clinical biochemical measurements further strengthen risk characterization. Cholesterol and glucose concentration levels offer meaningful insight into vascular condition and metabolic regulation. Elevated cholesterol accumulation contributes to arterial narrowing and plaque formation, whereas glucose imbalance often accelerates vascular complications. Combined metabolic burden may be represented as:

$$M_r = C_l + G_l \tag{4}$$

where $M_r$denotes metabolic risk contribution, $C_l$represents cholesterol level, and $G_l$corresponds to glucose concentration. Such measurements enrich cardiovascular profiling by reflecting biochemical disturbances associated with long-term disease progression.

Behavioral and lifestyle attributes remain equally important because cardiovascular risk frequently emerges through cumulative lifestyle influence. Smoking, alcohol intake, and physical inactivity collectively alter circulatory efficiency, endothelial function, and systemic inflammation. A simplified lifestyle burden function may be represented as:

$$L_b = S_h + A_i - P_a \tag{5}$$

where $L_b$denotes lifestyle burden, $S_h$represents smoking habit, $A_i$indicates alcohol intake, and $P_a$reflects physical activity participation. Increased lifestyle burden generally intensifies cardiovascular vulnerability, particularly when accompanied by metabolic imbalance.

Demographic attributes contribute another clinically meaningful dimension during acquisition. Age strongly influences cardiovascular susceptibility because arterial elasticity, cardiac performance, and metabolic efficiency gradually change across lifespan. Cardiovascular exposure tendency may therefore be represented as:

$$R_a = \alpha \cdot Age \tag{6}$$

where $R_a$represents age-associated cardiovascular susceptibility and αdenotes proportional cardiovascular influence. Such demographic inclusion improves physiological context during predictive modeling.

Clinical data acquisition further requires consistent representation of disease status to support supervised cardiovascular classification. The target variable is represented as:

$$Y \in \{0,1\} \tag{7}$$

where $Y = 0$denotes absence of cardiovascular disease risk and $Y = 1$represents cardiovascular disease presence. Binary target assignment provides the predictive reference required for subsequent VQC-based classification learning.

Careful acquisition of clinically grounded, multidimensional cardiovascular information strengthens the physiological consistency of downstream quantum learning stages by ensuring meaningful representation of

cardiovascular interactions, metabolic dependencies, vascular conditions, and behavioral influence within a medically interpretable feature space.

3.2. Clinical Data Harmonization

Clinical Data Harmonization strengthens the physiological consistency of acquired cardiovascular information by transforming heterogeneous medical observations into a structured and computationally stable representation suitable for downstream quantum learning. Cardiovascular records commonly contain variables originating from distinct medical scales, measurement units, and clinical distributions. Age appears in years, blood pressure values are measured in millimeters of mercury, biochemical indicators follow categorical clinical ranges, whereas lifestyle variables exist in binary or ordinal forms. Such variation introduces disproportionate feature influence, making harmonization essential for preserving balanced cardiovascular representation before quantum feature encoding.

The harmonization process begins through systematic examination of data completeness because incomplete medical observations can distort cardiovascular interpretation. Missing clinical entries frequently arise from inconsistent hospital documentation, laboratory omission, or interrupted patient evaluation. Let the missing ratio of a feature be represented as:

$$M_r = \frac{N_m}{N_t} \tag{8}$$

where $M_r$denotes missing ratio, $N_m$represents missing observations, and $N_t$indicates total observations within a clinical attribute. Elevated missing ratios weaken physiological continuity and reduce learning reliability; therefore, controlled treatment of incomplete values becomes necessary to preserve medical coherence.

Following completeness verification, distribution irregularities require careful attention because cardiovascular datasets often contain physiologically extreme observations. Blood pressure, cholesterol, and glucose measurements occasionally exhibit unusual deviations caused by temporary physiological conditions or recording inconsistencies. Detection of abnormal distributions is mathematically expressed using z-score standardization is shown in Figure 1.

$$z = \frac{x_v - \mu}{\sigma} \tag{9}$$

$$\mu = 0.0$$

$$x_v = 1.2$$

$$\sigma = 1.0$$

$$z = \frac{x_v - \mu}{\sigma} \approx 0.4$$

$$\Phi(z) \approx 65.5\%$$

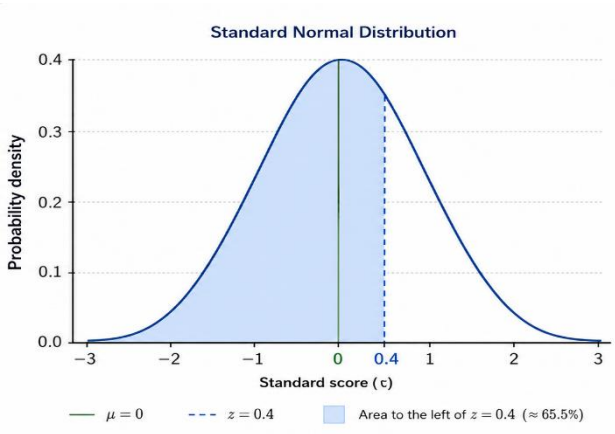


Figure 1. Z Score

where $x_v$represents the observed clinical value, μdenotes feature mean, and σindicates standard deviation. Extreme values exceeding acceptable physiological boundaries are carefully evaluated to avoid unnecessary removal of medically meaningful cardiovascular signals.

Feature scaling then becomes essential because quantum encoding remains highly sensitive to disproportionate numerical ranges. Clinical attributes with larger magnitudes may dominate learning behavior, thereby suppressing meaningful influence from moderate-scale physiological indicators. Standardization ensures balanced representation by transforming features toward a common statistical distribution:

$$x' = \frac{x - \mu}{\sigma} \tag{10}$$

where x'denotes standardized clinical representation. Such transformation prevents dominance of variables such as systolic blood pressure over lower numerical indicators including glucose categories or lifestyle observations.

Normalization further stabilizes feature distributions by restricting values within a bounded numerical interval compatible with quantum encoding requirements. Min-max scaling provides controlled feature compression and is mathematically represented as:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{11}$$

where $x_n$denotes normalized feature value, x_{min}represents minimum feature magnitude, and x_{max}indicates maximum feature magnitude. Controlled scaling becomes particularly important because variational quantum circuits operate efficiently when encoded values remain within stable rotational ranges.

Clinical consistency across cardiovascular variables also requires categorical harmonization. Cholesterol, glucose level, smoking habit, alcohol intake, and physical activity often exist as categorical medical indicators. Numerical transformation becomes necessary to preserve compatibility with quantum computational structures. Binary lifestyle variables are represented as:

$$L_v \in \{0,1\} \tag{11}$$

where $L_v = 0$indicates absence of behavioral exposure and $L_v = 1$denotes presence of cardiovascular influence. Such conversion preserves interpretability while maintaining computational readiness.

Inter-variable balance remains another important harmonization objective because cardiovascular vulnerability rarely develops through isolated physiological disturbances. Harmonized cardiovascular representation seeks proportional interaction among hemodynamic, metabolic, demographic, and behavioral indicators. Composite feature stability may be represented as:

$$H_s = \sum_{i=1}^{n} w_i \, x_i \tag{12}$$

where $H_s$denotes harmonized cardiovascular structure, $w_i$represents feature contribution weight, and $x_i$corresponds to normalized clinical variables. Balanced contribution improves physiological realism and strengthens downstream discriminative learning.

Class distribution assessment also forms part of harmonization because cardiovascular records occasionally exhibit unequal disease prevalence. Imbalanced disease representation may bias predictive learning toward dominant cardiovascular outcomes. Distribution balance is represented as:

$$D_b = \frac{N_p}{N_n} \tag{13}$$

where $D_b$denotes dataset balance ratio, $N_p$indicates positive cardiovascular observations, and $N_n$represents negative clinical observations. Controlled balancing improves predictive fairness and strengthens sensitivity toward vulnerable cardiovascular populations.

Clinical Data Harmonization therefore transforms multidimensional cardiovascular observations into a medically coherent, statistically stable, and quantum-compatible structure by ensuring completeness, physiological consistency, balanced scaling, categorical alignment, and proportional feature representation required for reliable variational quantum learning.

3.3. Stratified Data Partitioning

Stratified Data Partitioning organizes harmonized cardiovascular information into balanced learning subsets to establish reliable predictive behavior during variational quantum learning. Cardiovascular datasets frequently contain unequal disease distributions, where healthy observations may substantially outnumber cardiovascular-

positive cases. Such imbalance often introduces predictive bias, causing computational models to favor dominant categories while overlooking physiologically vulnerable populations. Careful partitioning therefore becomes necessary to preserve proportional cardiovascular representation and maintain reliable classification performance across heterogeneous patient groups.

The partitioning process begins through assessment of disease distribution within the harmonized cardiovascular dataset. Let the complete dataset be represented as:

$$D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \tag{14}$$

Where$x_n$denotes harmonized cardiovascular features and $y_n$represents associated cardiovascular status. The target label remains binary, reflecting cardiovascular absence or cardiovascular presence. Distribution assessment ensures that disease prevalence remains proportionally preserved throughout subsequent partitioning operations.

Class proportion estimation forms an important requirement because cardiovascular imbalance may distort predictive stability during quantum learning. Disease prevalence ratio is mathematically represented as:

$$P_c = \frac{N_c}{N_t} \tag{15}$$

where $P_c$denotes cardiovascular class proportion, $N_c$represents observations belonging to a specific disease class, and $N_t$indicates total dataset observations. Preservation of $P_c$across partitioned subsets prevents class dominance and strengthens cardiovascular sensitivity during classification.

Stratification then separates harmonized observations into learning subsets while preserving cardiovascular distribution consistency. Instead of random partitioning, stratified allocation maintains equal disease representation within each subset. The partitioning function is represented as:

$$D = D_{train} \cup D_{test} \tag{16}$$

subject to:

$$D_{train} \cap D_{test} = \emptyset \tag{17}$$

where D_{train}represents the training subset and D_{test}denotes the testing subset. Non-overlapping separation prevents data leakage and ensures independent cardiovascular evaluation during model validation.

Training partition formation supports quantum learning by exposing the VQC-HQCL framework to representative cardiovascular relationships. Sufficient training representation strengthens learning of hidden physiological dependencies among blood pressure, metabolic condition, body composition, and behavioral indicators. Training proportion is mathematically represented as:

$$R_t = \frac{N_{train}}{N_t} \tag{18}$$

where $R_t$denotes training ratio and N_{train}represents training observations. Controlled allocation improves model stability while preserving sufficient physiological diversity required for nonlinear cardiovascular learning.

Testing partition formation remains equally important because predictive reliability must be evaluated on previously unseen cardiovascular observations. Testing ratio is represented as:

$$R_e = \frac{N_{test}}{N_t} \tag{19}$$

where $R_e$denotes testing proportion and N_{test}indicates testing observations. Independent evaluation strengthens scientific reliability by measuring cardiovascular classification behavior beyond memorized training patterns.

Distribution preservation across subsets remains central to stratified partitioning because disproportionate class separation may distort disease recognition. Stratified consistency is mathematically maintained through:

$$P_{train}(y = c) \approx P_{test}(y = c) \tag{20}$$

where $P_{train}(y = c)$denotes cardiovascular class probability in the training partition and $P_{test}(y = c)$indicates disease probability in the testing partition. Comparable probability distribution strengthens predictive fairness and prevents disproportionate cardiovascular exposure.

Cross-validation integration further enhances learning robustness during stratified partitioning. Instead of relying upon a single training–testing separation, repeated subset rotation allows broader physiological learning exposure. Stratified k-fold representation may be expressed as:

$$D = \bigcup_{i=1}^{k} D_i \tag{21}$$

where $D_i$represents each stratified fold and $k$denotes the number of partition groups. Controlled rotational validation improves generalization by reducing dependence upon specific data arrangements.

Cardiovascular learning reliability additionally depends upon preserving medically meaningful diversity across all subsets. Age distribution, blood pressure variability, metabolic condition, and lifestyle behavior must remain proportionally distributed to avoid demographic dominance. Balanced partitioning therefore supports physiologically realistic cardiovascular representation throughout downstream variational quantum learning and hybrid optimization.

Stratified Data Partitioning consequently establishes a balanced computational environment by preserving cardiovascular class proportions, preventing data leakage, maintaining physiological diversity, supporting independent evaluation, and ensuring reliable exposure of harmonized cardiovascular information required for stable VQC-HQCL cardiovascular risk classification.

3.4. Quantum Feature Encoding

Quantum Feature Encoding transforms harmonized cardiovascular information into a quantum-compatible representation suitable for variational quantum learning. Cardiovascular observations collected through clinical examination naturally exist within a classical computational structure, where physiological indicators are represented through numerical values, categorical ranges, and behavioral labels. Variational quantum circuits, however, operate through quantum states governed by rotational transformations and probabilistic representations. Such structural incompatibility requires an intermediate transformation stage capable of preserving cardiovascular information while enabling stable interaction within the quantum computational environment.

The encoding process begins by representing the harmonized cardiovascular dataset as a structured feature vector. Let the normalized cardiovascular feature space be represented as:

$$X = [x_1, x_2, x_3, \ldots, x_n] \tag{22}$$

where Xdenotes the complete harmonized cardiovascular profile and $x_n$represents normalized physiological or behavioral variables associated with cardiovascular risk. Since variational quantum circuits process rotational quantum states, direct insertion of classical medical values becomes computationally infeasible. Quantum feature encoding therefore performs systematic transformation of cardiovascular attributes into quantum state parameters.

Angle encoding is selected as the primary encoding strategy because cardiovascular datasets typically consist of structured tabular observations with moderate dimensionality. Such representation allows continuous physiological information to influence rotational quantum gates efficiently without introducing excessive computational burden. Encoded quantum rotation is mathematically represented as:

$$R(\theta_i) = R(x_i) \tag{23}$$

where $R(\theta_i)$denotes rotational quantum transformation and $x_i$represents the corresponding normalized cardiovascular feature. Each physiological observation therefore contributes directly to quantum state formation through controlled angular transformation.

Normalized cardiovascular variables are subsequently translated into rotation angles to preserve proportional physiological contribution. Angular representation is defined as:

$$\theta_i = \pi x_i \tag{24}$$

where $\theta_i$represents encoded quantum rotation and $x_i$corresponds to normalized cardiovascular observations constrained within bounded numerical intervals. Controlled angular mapping ensures computational stability by preventing excessive quantum oscillation during circuit learning.

Following rotational transformation, cardiovascular information is embedded into qubit states through quantum superposition. A single encoded qubit state may be expressed as:

$$| \psi\rangle = cos\left(\frac{\theta}{2}\right) | 0\rangle + sin\left(\frac{\theta}{2}\right) | 1\rangle \tag{25}$$

where $| \psi\rangle$denotes encoded cardiovascular representation, while $| 0\rangle$and $| 1\rangle$represent quantum basis states. Such representation enables simultaneous probabilistic encoding of physiological characteristics instead of rigid binary storage. Cardiovascular information therefore becomes embedded within amplitude relationships governed by encoded clinical measurements.

Feature interaction becomes especially important because cardiovascular abnormalities rarely emerge from isolated medical indicators. Elevated blood pressure alone may not indicate meaningful cardiovascular instability without simultaneous metabolic disruption or behavioral influence. Quantum encoding therefore preserves multidimensional physiological dependency by embedding correlated cardiovascular information into interconnected qubit structures. Composite encoding interaction may be represented as:

$$Q_f = \sum_{i=1}^{n} \theta_i \, q_i \tag{26}$$

where $Q_f$denotes encoded cardiovascular quantum representation and $q_i$indicates individual qubit contributions influenced by encoded rotational parameters. Such transformation improves representation of nonlinear physiological dependencies within downstream quantum learning.

Entanglement-assisted representation further strengthens encoded cardiovascular relationships by allowing interaction among multiple physiological indicators. Interconnected metabolic and hemodynamic dependencies become computationally meaningful through coupled quantum representation. Pairwise cardiovascular interaction may be represented as:

$$E_{ij} = q_i \otimes q_j \tag{27}$$

where E_{ij}denotes entangled cardiovascular interaction between qubits $q_i$and q_j. Such coupling supports richer representation of cardiovascular dependencies associated with blood pressure, cholesterol accumulation, glucose variation, and behavioral exposure.

Quantum state preparation additionally ensures dimensional compatibility with downstream variational quantum learning. The final encoded cardiovascular representation may therefore be expressed as:

$$| \Psi(X)\rangle = U(X) | 0\rangle^{\otimes n} \tag{28}$$

where $U(X)$denotes quantum encoding transformation applied to harmonized cardiovascular features and $| 0\rangle^{\otimes n}$represents initialized qubit states. Controlled preparation ensures physiologically meaningful cardiovascular information remains computationally accessible during subsequent VQC learning.

Quantum Feature Encoding therefore establishes a medically consistent and computationally stable bridge between harmonized cardiovascular observations and variational quantum circuits by translating normalized physiological indicators into structured quantum representations capable of preserving nonlinear cardiovascular dependencies required for reliable cardiovascular risk classification.

3.5. Variational Quantum Learning (VQC)

Variational Quantum Learning establishes the predictive learning core of the VQC-HQCL framework by enabling encoded cardiovascular information to undergo adaptive quantum transformation for risk-sensitive pattern discovery. Following quantum feature encoding, harmonized cardiovascular attributes become embedded into qubit states, yet meaningful classification cannot emerge without a trainable mechanism capable of identifying hidden physiological interactions. Variational Quantum Classifier learning therefore functions as a structured optimization process through which encoded cardiovascular representations evolve toward discriminative cardiovascular boundaries.

The variational learning process begins through initialization of a parameterized quantum circuit designed to process encoded cardiovascular states. Let the encoded cardiovascular quantum representation be expressed as:

$$| \Psi(X) \rangle \tag{29}$$

where $| \Psi(X) \rangle$denotes the encoded cardiovascular state generated from harmonized medical features. Variational learning applies trainable transformations over this encoded representation through parameterized quantum gates governed by adjustable quantum parameters.

The trainable variational circuit is mathematically represented as:

$$U(\theta) = U_L(\theta_L)U_{L-1}(\theta_{L-1}) \dots U_1(\theta_1) \tag{30}$$

where $U(\theta)$denotes the variational quantum circuit, Lrepresents the circuit depth, and θcorresponds to trainable quantum parameters. Each transformation layer gradually reshapes encoded cardiovascular information into increasingly discriminative internal representations.

Rotational quantum gates form an essential component within variational learning because cardiovascular information encoded through angle transformation naturally aligns with rotational parameter updates. Parameterized gate operations may be represented as:

$$R_y(\theta) = \begin{bmatrix} cos(\theta/2) & -sin(\theta/2) \\ sin(\theta/2) & cos(\theta/2) \end{bmatrix} \tag{31}$$

where $R_y(\theta)$denotes parameterized rotational transformation governed by trainable angle θ. Controlled adjustment of rotational states enables flexible learning of cardiovascular dependencies associated with blood pressure variability, metabolic imbalance, and behavioral burden.

Entanglement layers further strengthen cardiovascular learning by establishing interdependence among encoded physiological indicators. Since cardiovascular abnormalities emerge through accumulated interaction among multiple risk contributors, independent processing of isolated features may reduce physiological realism. Entanglement interaction may be represented as:

$$| \Phi \rangle = U_E | \Psi(X) \rangle \tag{32}$$

where $U_E$denotes entanglement transformation applied to encoded cardiovascular states. Such interaction enables correlated learning among hemodynamic, metabolic, demographic, and behavioral attributes, strengthening nonlinear cardiovascular representation.

Following variational transformation, quantum measurement generates probabilistic prediction values associated with cardiovascular classification. Expected measurement output is mathematically represented as:

$$f(X, \theta) = \langle \Psi(X) | U^{\dagger}(\theta) M U(\theta) | \Psi(X) \rangle \tag{33}$$

where $f(X, \theta)$represents prediction response, Mdenotes measurement operator, and $U^{\dagger}(\theta)$indicates conjugate circuit transformation. Measurement expectation therefore converts quantum state evolution into clinically interpretable cardiovascular prediction behavior.

Learning progression depends strongly upon continuous refinement of variational parameters. Cardiovascular discrimination improves gradually through repeated parameter adjustment aimed at minimizing predictive inconsistency. Classification error is quantified through a suitable loss function represented as:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{34}$$

where $L(\theta)$denotes prediction loss, $y_i$represents actual cardiovascular class, and $\hat{y}_i$indicates predicted cardiovascular output. Loss minimization guides parameter adaptation toward improved cardiovascular sensitivity.

Gradient-guided parameter refinement then modifies circuit behavior to strengthen disease discrimination. Parameter updates are mathematically represented as:

$$\theta_{new} = \theta_{old} - \eta\nabla L(\theta) \tag{35}$$

where ηdenotes learning rate and $\nabla L(\theta)$represents gradient information associated with prediction loss. Progressive adjustment improves cardiovascular boundary formation across repeated learning cycles.

Decision-oriented cardiovascular representation emerges through learned probability distributions reflecting disease vulnerability. Final prediction probability is represented as:

$$P(y = 1 \mid X) = \sigma(f(X, \theta)) \tag{36}$$

where $P(y = 1 \mid X)$denotes cardiovascular disease probability and σrepresents activation mapping over learned quantum output. Such transformation supports physiologically meaningful cardiovascular discrimination by assigning measurable disease likelihood to encoded patient conditions.

Variational Quantum Learning therefore strengthens predictive cardiovascular representation through parameterized quantum transformation, entangled physiological interaction learning, adaptive circuit refinement, probabilistic disease estimation, and progressive optimization of encoded cardiovascular states required for stable cardiovascular risk classification.

3.6. Hybrid Quantum Optimization (HQCL)

Hybrid Quantum Optimization governs the adaptive learning behavior of the VQC-HQCL framework by coordinating interaction between quantum computation and classical optimization for stable cardiovascular risk learning. Variational quantum learning generates probabilistic cardiovascular predictions through parameterized quantum circuits; however, meaningful cardiovascular discrimination cannot emerge without systematic parameter refinement. Hybrid optimization therefore establishes an iterative learning structure through which quantum-generated cardiovascular representations are continuously improved using classical computational guidance.

The optimization process begins immediately after variational quantum learning produces measurement-based cardiovascular outputs. Let the predicted cardiovascular response generated from the variational circuit be represented as:

$$\hat{y} = f(X, \theta) \tag{37}$$

where $\hat{y}$denotes predicted cardiovascular output, Xrepresents encoded cardiovascular features, and θcorresponds to trainable variational parameters governing circuit behavior. Since prediction quality depends strongly upon parameter suitability, continuous refinement becomes necessary to align learned cardiovascular boundaries with clinically meaningful disease patterns.

Cardiovascular prediction inconsistency is quantified through objective loss estimation. The optimization mechanism evaluates deviation between predicted cardiovascular status and actual cardiovascular class labels to identify learning error. Binary cross-entropy loss provides suitable cardiovascular classification guidance and is represented as:

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}[y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)] \tag{38}$$

where $L(\theta)$denotes classification loss, $y_i$represents true cardiovascular status, and $\hat{y}_i$indicates predicted disease probability. Reduced loss magnitude generally reflects stronger cardiovascular separation capacity.

Following loss evaluation, classical optimization mechanisms estimate parameter sensitivity to improve cardiovascular prediction behavior. Since variational quantum circuits cannot independently adjust internal parameters efficiently, classical optimizers perform corrective adaptation through gradient-guided refinement. Parameter sensitivity may be represented as:

$$g(\theta) = \frac{\partial L(\theta)}{\partial \theta} \tag{39}$$

where $g(\theta)$denotes gradient contribution associated with trainable quantum parameters. Gradient estimation identifies parameter directions contributing toward improved cardiovascular discrimination.

Hybrid optimization proceeds through controlled parameter adjustment aimed at minimizing cardiovascular prediction inconsistency. Updated variational parameters are mathematically represented as:

$$\theta_{t+1} = \theta_t - \eta g(\theta_t) \tag{40}$$

where $\theta_t$denotes existing circuit parameters, ηrepresents optimization learning rate, and θ_{t+1}indicates refined cardiovascular learning parameters. Progressive parameter adaptation strengthens the ability of the quantum circuit to capture hidden cardiovascular interactions.

Quantum circuit execution then resumes using updated parameters generated through classical optimization. The revised variational transformation is represented as:

$$| \Psi_{t+1} \rangle = U(\theta_{t+1}) | \Psi(X) \rangle \tag{41}$$

where $| \Psi_{t+1} \rangle$denotes updated cardiovascular quantum representation after optimization. Iterative re-execution strengthens discriminative cardiovascular structure while gradually reducing classification instability.

Convergence assessment forms another important component of hybrid optimization because excessive circuit updates may introduce instability rather than improvement. Optimization stability is monitored through convergence criteria represented as:

$$| L_{t+1} - L_t | < \epsilon \tag{42}$$

where ϵdenotes acceptable optimization tolerance. Controlled convergence ensures stable cardiovascular learning without unnecessary computational fluctuation.

Quantum-classical interaction remains central to HQCL because current quantum systems possess limited qubit stability, noise sensitivity, and restricted circuit depth. Hybrid learning therefore distributes computational responsibility between complementary environments. Quantum computation supports nonlinear cardiovascular representation through probabilistic state evolution, while classical computation contributes stable optimization behavior and parameter correction. Combined learning contribution may be represented as:

$$H_{opt} = Q_c + C_o \tag{43}$$

where H_{opt}denotes hybrid optimization structure, $Q_c$represents quantum computational learning, and $C_o$indicates classical optimization support. Such integration improves computational practicality while preserving cardiovascular learning depth.

Iterative refinement ultimately strengthens discrimination among subtle cardiovascular patterns influenced by blood pressure, metabolic imbalance, demographic variability, and behavioral exposure. Cardiovascular vulnerability often emerges through nonlinear physiological relationships that remain difficult to capture using isolated statistical assumptions. Hybrid Quantum Optimization therefore strengthens predictive stability by repeatedly aligning variational quantum learning toward clinically meaningful cardiovascular separation through loss minimization, parameter refinement, convergence monitoring, and coordinated interaction between quantum representation and classical computational correction.

6.7. Cardiovascular Risk Classification

Cardiovascular Risk Classification transforms optimized quantum learning outcomes into clinically interpretable cardiovascular predictions by assigning disease-sensitive labels to encoded patient conditions. Following hybrid quantum optimization, variational quantum learning gradually develops refined decision boundaries capable of distinguishing cardiovascular vulnerability from physiologically stable conditions. Cardiovascular classification therefore serves as the predictive stage through which learned cardiovascular patterns become medically meaningful risk assignments suitable for computational cardiovascular screening.

The classification process begins through extraction of optimized quantum measurement responses generated by the trained VQC-HQCL framework. Let the optimized quantum prediction score be represented as:

$$z_p = f(X, \theta^*) \tag{44}$$

where $z_p$denotes optimized cardiovascular prediction output, Xrepresents encoded cardiovascular features, and θ^*indicates optimized variational parameters obtained through hybrid quantum optimization. Such prediction values carry probabilistic cardiovascular information rather than direct categorical labels, requiring controlled transformation into clinically interpretable cardiovascular classes.

Probability estimation then converts optimized quantum outputs into bounded cardiovascular likelihood scores. Sigmoid transformation is adopted because cardiovascular classification operates through binary disease representation. Probability estimation may therefore be expressed as:

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-z}} \tag{45}$$

where $P(y = 1 \mid X)$denotes cardiovascular disease probability conditioned upon encoded cardiovascular observations. Such transformation converts learned quantum responses into interpretable cardiovascular likelihood ranging between zero and one.

Risk probability interpretation becomes essential because cardiovascular abnormalities often emerge through accumulated physiological burden rather than isolated disturbances. Elevated blood pressure, cholesterol variation, metabolic imbalance, reduced physical activity, and behavioral burden collectively influence disease susceptibility. Learned quantum representations therefore evaluate hidden nonlinear cardiovascular dependencies and translate such interactions into measurable disease risk. Composite cardiovascular contribution may be represented as:

$$\mathrm{R_c} = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{w_i}\, \mathrm{x_i} \tag{46}$$

where $\mathrm{R_c}$denotes cardiovascular contribution score, $\mathrm{w_i}$represents learned feature importance, and $\mathrm{x_i}$corresponds to harmonized cardiovascular indicators. Such internal representation strengthens physiological sensitivity during classification.

Threshold-based decision assignment subsequently converts probability estimates into cardiovascular class labels. Binary cardiovascular prediction follows decision thresholding represented as:

$$\hat{\mathrm{y}} = \begin{cases} 1, & \mathrm{P(y = 1 \mid X)} \geq \tau \\ 0, & \mathrm{P(y = 1 \mid X)} < \tau \end{cases} \tag{47}$$

where $\hat{\mathrm{y}}$denotes predicted cardiovascular class and τrepresents classification threshold. Controlled threshold selection strengthens classification fairness by balancing disease sensitivity and healthy population specificity.

Decision threshold calibration remains clinically important because cardiovascular screening seeks balanced identification of vulnerable patients while reducing unnecessary misclassification. Threshold selection may be refined through optimization of discriminative sensitivity represented as:

$$\mathrm{T_{opt}} = \arg\max(\mathrm{Sensitivity} + \mathrm{Specificity}) \tag{48}$$

where $\mathrm{T_{opt}}$denotes optimized cardiovascular decision threshold. Such calibration improves predictive reliability by preserving physiological realism during disease assignment.

Cardiovascular classification behavior further depends upon learned separation boundaries generated during variational quantum optimization. Decision surfaces emerge through nonlinear interaction among encoded cardiovascular indicators rather than isolated statistical assumptions. Learned classification boundary may be represented as:

$$D(X) = \text{sign}(f(X, \theta^*)) \tag{49}$$

where $D(X)$denotes cardiovascular decision function. Nonlinear separation strengthens sensitivity toward subtle cardiovascular susceptibility patterns that may remain hidden under conventional linear discrimination.

Prediction confidence additionally contributes meaningful computational interpretation during cardiovascular classification. Confidence estimation quantifies certainty associated with assigned disease labels and may be represented as:

$$C_f = | P(y = 1 \mid X) - 0.5 | \tag{50}$$

where $C_f$denotes prediction confidence magnitude. Higher confidence values generally indicate stronger cardiovascular distinction between healthy and vulnerable physiological states.

Classification reliability depends strongly upon stable preservation of learned cardiovascular interactions generated during quantum optimization. Cardiovascular disease commonly develops through multidimensional physiological burden involving vascular stress, metabolic irregularity, demographic susceptibility, and behavioral exposure. Optimized VQC-HQCL learning therefore supports cardiovascular classification by transforming encoded physiological interactions into clinically interpretable disease probabilities, threshold-sensitive risk assignments, nonlinear decision boundaries, and confidence-aware cardiovascular prediction behavior suitable for reliable cardiovascular risk assessment.

4. Dataset Description

The Cardiovascular Disease dataset is a publicly available clinical dataset obtained from Kaggle for cardiovascular risk prediction and binary disease classification. The dataset contains 70,000 patient records, with each record representing one individual examined through routine cardiovascular assessment. The data source is listed as Kaggle under the title Cardiovascular Disease Dataset by Sulianova.The dataset includes demographic, physiological, metabolic, and lifestyle-related attributes required for structured cardiovascular analysis. Clinically usable input features include age, gender, height, weight, systolic blood pressure, diastolic blood pressure, cholesterol level, glucose level, smoking habit, alcohol intake, and physical activity status. The target variable, cardio, indicates the presence or absence of cardiovascular disease, where binary labeling supports supervised classification.

Age and gender provide demographic context, while height and weight support body-composition-based assessment. Systolic and diastolic blood pressure describe hemodynamic condition. Cholesterol and glucose levels represent metabolic influence associated with vascular risk. Smoking, alcohol intake, and physical activity describe lifestyle exposure affecting cardiovascular stability.For the proposed VQC-HQCL framework, this dataset provides a structured clinical foundation for cardiovascular risk classification. The combination of physiological and behavioral indicators supports nonlinear interaction learning through quantum feature encoding and variational quantum classification.

5. Results and Discussions

This section presents the analytical interpretation of cardiovascular classification performance obtained through the proposed Variational Quantum Classifier with Hybrid Quantum-Classical Learning framework. Performance assessment is conducted using accuracy, F-measure, precision, recall, AUC-ROC, and specificity. Comparative examination against QHF-CS and QDCNN establishes predictive reliability, discrimination strength, and screening suitability. Observed performance patterns clarify the contribution of quantum feature representation and hybrid variational optimisation in cardiovascular risk classification within structured clinical data environments.

Classification accuracy measures the proportion of correctly classified cardiovascular records, whereas F-measure expresses the balanced performance of precision and recall; higher values indicate stronger and more dependable cardiovascular risk recognition. In Figure 2, the x-axis represents the classification algorithms, namely QHF-CS, QDCNN, and VQC-HQCL, while the y-axis represents performance percentage for classification accuracy and F-measure. QHF-CS recorded the lowest performance, with 63.420% accuracy and

65.494% F-measure. Such limited performance may arise from rigid feature-space separation, where subtle interactions among physiological and lifestyle attributes remain insufficiently preserved. QDCNN improved performance to 67.745% accuracy and 69.891% F-measure; however, convolution-driven representation over structured clinical variables may introduce locality assumptions that are less suitable for non-spatial cardiovascular attributes. The proposed VQC-HQCL achieved the highest accuracy of 82.394% and F-measure of 83.652%, exceeding QDCNN by 14.649 and 13.761 percentage points, respectively. The principal advantage of VQC-HQCL lies in interaction-preserving variational refinement, where encoded cardiovascular attributes are adaptively processed through quantum circuit learning and classically optimized parameter updates. Such coordinated learning supports stronger discrimination of nonlinear risk relationships, producing superior cardiovascular classification performance.

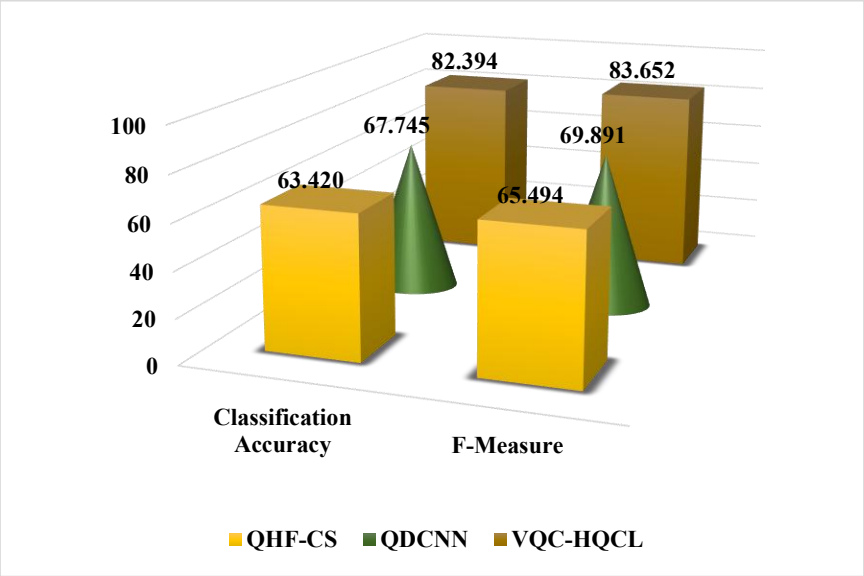


Figure 2. Classification Accuracy and F-Measure

Precision measures the proportion of cardiovascular-risk predictions that are correctly identified, reflecting the reliability of positive classification. Recall measures the proportion of actual cardiovascular-risk cases successfully detected, indicating the model's sensitivity toward clinically vulnerable records. Higher precision reduces unnecessary false alerts, whereas higher recall reduces missed cardiovascular-risk cases. In Figure 3, the x-axis represents the classification algorithms, namely QHF-CS, QDCNN, and VQC-HQCL, while the y-axis denotes precision and recall values expressed in percentage. QHF-CS obtained 60.996% precision and 70.709% recall, suggesting increased false-positive assignments caused by inadequate separation of overlapping cardiovascular profiles. QDCNN achieved 66.327% precision and 73.861% recall; nevertheless, fixed hierarchical extraction may weaken recognition of dispersed clinical dependencies across metabolic and lifestyle variables. The proposed VQC-HQCL recorded the highest precision of 80.430% and recall of 87.143%, outperforming QDCNN by 14.103 and 13.282 percentage points, respectively. The distinctive advantage of VQC-HQCL arises from risk-sensitive interaction consolidation, where variational quantum learning jointly refines interdependent cardiovascular indicators under hybrid optimization. Such refinement improves positive-risk reliability while preserving strong sensitivity toward actual cardiovascular-risk cases.

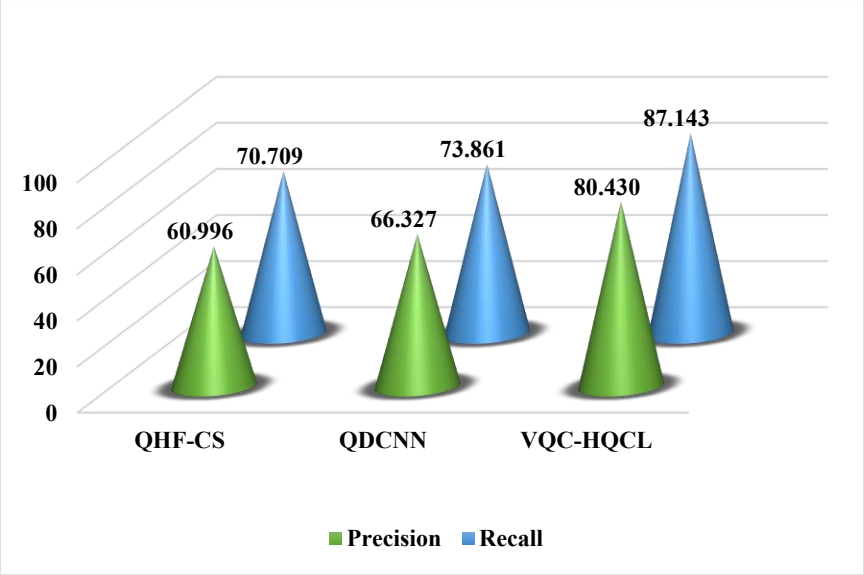


Figure 3. Precision and Recall

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) measures the ability of a classifier to distinguish cardiovascular-risk cases from non-risk cases across varying decision thresholds. Values approaching 1 indicate stronger ranking capability and more reliable discrimination, whereas values near 0.5 reflect weak separability. In Figure 4, the x-axis represents the classification algorithms, namely QHF-CS, QDCNN, and VQC-HQCL, while the y-axis denotes AUC-ROC values. QHF-CS achieved an AUC-ROC of 0.635, indicating modest discriminative ability; such behaviour may be associated with restricted probability ordering when clinically similar records occupy overlapping regions. QDCNN increased the value to 0.677, although compressed confidence separation among heterogeneous tabular attributes may limit threshold-independent discrimination. The proposed VQC-HQCL attained the highest AUC-ROC of 0.822, exceeding QDCNN by 0.145 and QHF-CS by 0.187. The notable advantage of VQC-HQCL lies in threshold-resilient risk score ordering, where quantum-encoded cardiovascular relationships and hybrid parameter optimization support clearer ranking of vulnerable records across multiple classification thresholds. Such performance confirms stronger discrimination stability for cardiovascular risk classification.

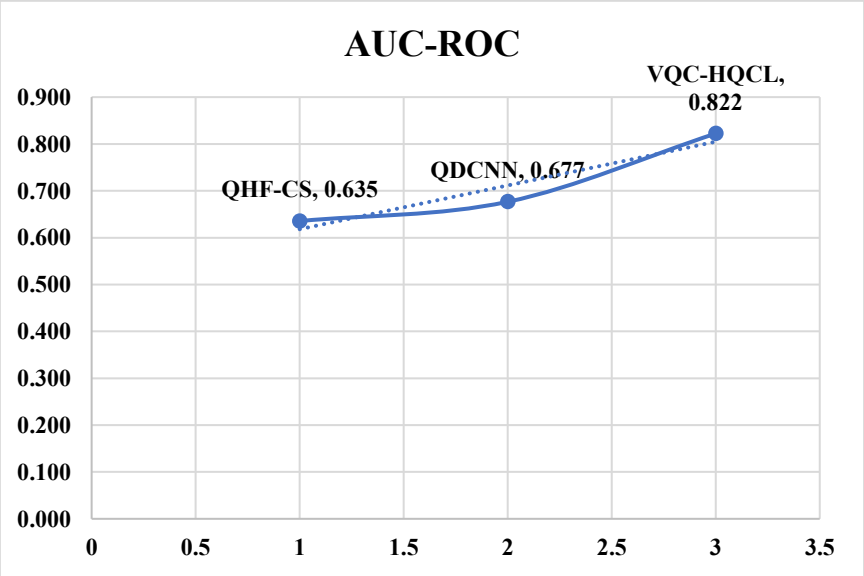


Figure 4. Area Under the Receiver Operating Characteristic Curve

Specificity measures the proportion of non-cardiovascular-risk records correctly identified as negative cases. Higher specificity indicates stronger ability to distinguish clinically non-risk profiles from cardiovascular-risk patterns, thereby reducing unnecessary alerts and supporting dependable screening decisions. In Figure 5, the x-

axis represents the classification algorithms, namely QHF-CS, QDCNN, and VQC-HQCL, while the y-axis denotes specificity values. QHF-CS recorded the lowest specificity of 0.564, indicating limited recognition of negative cardiovascular cases; such behaviour may arise from excessive boundary expansion toward the positive-risk class. QDCNN improved specificity to 0.615, although channel-weighted feature learning may preserve weak associations from borderline clinical attributes, increasing non-risk misclassification. The proposed VQC-HQCL achieved the highest specificity of 0.773, exceeding QDCNN by 0.158 and QHF-CS by 0.209. The principal advantage of VQC-HQCL lies in non-risk profile preservation, where variational quantum transformations retain finer interaction differences among physiologically stable records while hybrid optimization limits incorrect positive assignment. Such performance demonstrates improved exclusion capability for cardiovascular risk classification, strengthening clinical screening.

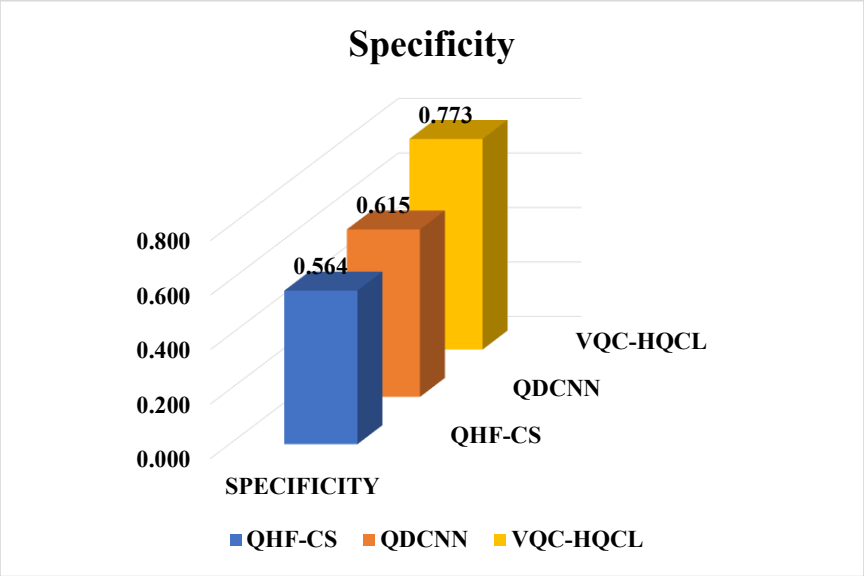


Figure 5. Specificity

6. Conclusion

Cardiovascular risk classification demands computational frameworks capable of recognising intricate relationships among demographic, physiological, metabolic, and lifestyle indicators. The proposed Variational Quantum Classifier with Hybrid Quantum-Classical Learning (VQC-HQCL) established a structured pathway for cardiovascular assessment through clinical data harmonisation, stratified partitioning, quantum feature encoding, variational quantum learning, hybrid optimisation, and risk-oriented classification. Quantum encoding transformed harmonised cardiovascular attributes into circuit-compatible representations, while variational quantum learning supported interaction-sensitive discrimination across complex clinical patterns. Hybrid optimisation strengthened parameter refinement through coordinated quantum circuit execution and classical corrective learning, enabling stable cardiovascular class separation.

Comparative evaluation against QHF-CS and QDCNN demonstrated consistently stronger predictive behaviour for VQC-HQCL across classification accuracy, F-measure, Fowlkes–Mallows Index, Matthews Correlation Coefficient, precision, recall, and AUC-ROC. Improved true positive recognition accompanied reduced false positive behaviour, lower false alarm occurrence, and stronger specificity. Such combined performance indicates balanced discrimination across cardiovascular-risk and non-risk records rather than improvement limited to a single evaluation dimension.

The principal contribution arises from interaction-preserving variational learning supported by hybrid quantum-classical optimisation. Such design strengthens representation of nonlinear cardiovascular dependencies associated with blood pressure, metabolic condition, body composition, and behavioural exposure. Clinical value lies in risk-assessment support for preventive screening and decision assistance, subject to independent validation, calibration assessment, explainability examination, and clinical governance before practical adoption, without overstating present-day quantum advantage in clinical practice. VQC-HQCL therefore offers a technically grounded quantum-assisted direction for reliable cardiovascular risk classification within intelligent healthcare analytics.

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