

HYBRID QUANTUM-CLASSICAL LEARNING FRAMEWORK FOR INTELLIGENT FEATURE OPTIMIZATION AND PREDICTIVE ANALYTICS IN ENGINEERING APPLICATIONS

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ABSTRACT

As the dimensionality and complexity of engineering data grows, traditional machine learning systems become increasingly difficult to apply, especially when detecting informative features without sacrificing predictive accuracy and computational efficiency. In this paper we proposed a Hybrid Quantum-Classical Learning Framework for Intelligent Feature Optimization and Predictive Analytics in Engineering Applications. The framework is a combination of classical data preprocessing, intelligent feature selection, quantum-enhanced feature representation, parameterized quantum circuits and predictive learning in a unified optimization pipeline. Engineering features are first normalized and evaluated to find informative subsets and minimize redundancy. These selected features are then mapped onto the quantum feature space and parameterized quantum circuits to create improved representations for predictive modeling. The optimization objective takes into account predictive loss, size of the feature subset and regularization to achieve an efficient feature configuration. This quantum-classical representation is fed to the classical predictive models for classification and evaluation of the models. The framework is assessed based on predictive accuracy, ROC properties, feature reduction, convergence behavior, computational time, scalability and prediction error. The potential of using intelligent feature optimization combined with quantum enhanced representation for engineering analytics is illustrated by comparing it to conventional machine learning and hybrid learning models. This study provides a flexible framework that enables the merging of quantum and classic machine learning, and shows how hybrid architectures can be used in high-dimensional engineering prediction.

Keywords: Hybrid Quantum-Classical Learning, Quantum Machine Learning, Intelligent Feature Optimization, Feature Selection, Parameterized Quantum Circuits, Quantum Feature Encoding, Predictive Analytics, Engineering Applications, Variational Quantum Algorithms, Machine Learning.

1. INTRODUCTION

Due to the very fast development of sensing, automation, cyber-physical systems, intelligent manufacturing, energy systems, robotics and other engineering applications, we have been inundated with ever-larger and more heterogeneous datasets [1]. These data sets often include numerical data, categorical attributes, correlated variables, redundant information, and nonlinear relationships that need to be analyzed to make accurate predictions and decisions [2]. In conventional data-driven engineering approaches, patterns are typically discovered using machine-learning approaches [3]. While these techniques have shown great promise, the value of their output is highly reliant on the quality and dimensionality of the feature space they are presented with. The more features, the more redundant and irrelevant attributes can actually lead to greater computational needs and can have negative impacts on the generalization capability of predictive models [4]. So intelligent feature optimization is now an integral part of engineering analytics in today's world.

Classical machine-learning techniques usually extract features, select features, and then conduct prediction modeling in the classical computational architecture. For structured data, the ensemble learning methods like XGBoost have been shown to be scalable and predictive, and are thus appropriate benchmarks for engineering prediction problems [5]. When the number of the candidate features is large, however, the search space grows exponentially, while traditional feature-selection methods can become computationally prohibitive [6]. In addition, engineering systems can contain complicated nonlinear relationships that may not be well captured with traditional feature transformations [7]. These restrictions have led to the development of alternative paradigms of computation that have the potential to offer better feature representation and more efficient optimization mechanisms [8].

Selected machine-learning and optimization problems have emerged as potential applications of quantum computing as a new paradigm for computation [9]. Quantum machine learning (QML) uses the ideas of quantum computation and machine-learning techniques to leverage quantum states, quantum

measurements, and parameterized quantum circuits in data processing [10].

The other line of research that is crucial is the use of quantum computing in the optimization of features [11]. Feature selection is one of the combinatorial optimization problems, where the goal is to find an informative set of features with minimum redundancy and computational complexity [12]. Another way of exploring these huge search spaces is by means of quantum optimization methods [13]. Enhanced representations can be generated by quantum feature-space methods and trainable quantum transformations can be optimized using variational quantum algorithms [14] and parameterized quantum circuits [15]. Increased interest in using quantum resources for not only prediction, but to enhance the feature selection stage [16], is also reflected in the research to date, which has begun to explore quantum-assisted feature selection and hybrid optimization strategies [17].

In engineering applications, feature optimization coupled with predictive analytics is crucial [18]. There can be many measurements from sensors, simulation, monitoring system and industrial processes in engineering datasets [19]. Not all measured attributes are equally important to the target prediction, and highly correlated attributes will not necessarily give much extra information but add complexity to the model [20]. An effective feature-optimization mechanism should therefore identify a compact and informative feature subset while preserving predictive information [21]. The resulting optimized representation can then be provided to a classical predictive model, allowing the quantum component to focus on feature transformation and optimization while the classical component performs robust prediction [22].

But previous research typically focuses on one of the three strands of this research path. Some studies deal mainly with quantum feature mapping [23] and others with parameterized quantum circuits, hybrid learning [24] or variational optimization [25]. Other research assesses quantum enhanced learning in particular application fields [26]. Therefore, a unified framework that explicitly incorporates intelligent feature optimization, quantum enhanced representation learning [27] and predictive analytics for general engineering applications is still needed. Furthermore, the evaluation should include statistical significance, optimization convergence, computational cost, and feature reduction as well as predictive accuracy [28].

In this regard, this work introduces a Hybrid Quantum-Classical Learning Framework for Intelligent Feature Optimization and Predictive Analytics in Engineering Applications to overcome these drawbacks. The proposed framework integrates classical data preprocessing and quantum feature encoding, parameterized quantum circuits, intelligent feature selection optimization and classical predictive learning. The engineering feature space is then normalized and preprocessed for quantum processing. The engineering feature space is then normalized and preprocessed for quantum processing. Candidates are then tested with a quantum-assisted optimization mechanism: a classical optimization process runs repeatedly with the quantum circuit. The optimized features are then converted to quantum

enhanced representations and fed to a classical predictive model for final prediction.

The main goal of the proposed framework is to assess if an optimized representation that is more compact and informative for engineering data can be obtained without compromising the predictive capabilities while using quantum assistance. The proposed approach is a hybrid one where preprocessing and final predictive learning is done in a classical computing architecture, and quantum computing is used for feature representation and optimization.

The proposed framework is assessed by various complementary metrics, such as the predictive accuracy, the percentage of feature reduction, computation time, optimization convergence, and statistical comparison with conventional machine-learning techniques. As a highly scalable algorithm for structured data, XGBoost is regarded as one of the classical prediction baselines. A set of statistical comparison procedures are embedded, based on the common methods used for comparing several classifiers and on multiple comparison significance control. This thorough assessment should establish whether or not the proposed hybrid architecture offers quantifiable benefits over prediction alone.

The main contributions of this work are summarized as follows:

1. A unified hybrid quantum-classical architecture is developed for intelligent feature optimization and predictive analytics in engineering applications.
2. A quantum-assisted feature optimization mechanism is incorporated to identify informative feature subsets while reducing redundant attributes.
3. A parameterized quantum feature-processing stage is integrated with a classical predictive-learning component to exploit complementary classical and quantum capabilities.
4. A multi-dimensional evaluation strategy is introduced that considers predictive performance, feature reduction, computational cost, convergence behavior, and statistical significance.
5. The proposed framework is designed to provide a general methodology that can be adapted to different structured engineering datasets and predictive-analysis tasks.

2. LITERATURE SURVEY

In recent years, efforts have been made to leverage quantum machine learning (QML) by combining quantum computing with traditional machine learning to enhance the representation of features, optimization of models, and prediction accuracy. In a comprehensive study of variational quantum algorithms (VQAs), Cerezo et al. [1] pointed out the need for parameterized quantum circuits and classical optimization methods for near-term quantum computers. Their work lays the groundwork for hybrid quantum-classical learning, where quantum circuits execute problem-specific

transformations, and classical optimizers adjust trainable parameters. Bharti et al. [2] continued to explore noisy intermediate-scale quantum (NISQ) algorithms and the constraints/limitations imposed by limited qubit numbers, noise, circuit depth, and optimization.

Another emerging area of interest in QML is quantum feature representation. The idea of quantum machine learning in feature Hilbert spaces was introduced by Schuld et al. [3] who showed that classical input signals could be encoded as high-dimensional quantum representation using quantum feature maps. Havlíček et al. [4] experimentally demonstrated the possibility of supervised learning with quantum-enhanced feature spaces, and how the quantum feature mapping can be combined with classical learning procedures. These methods are especially relevant to the case of predictive analytics because the quality of feature representations is directly related to the ability of the downstream learning models to be separated and predict future outcomes. Therefore, quantifying the features of the object allows for a possible way to convert traditional attributes of engineering into representations for hybrid predictive models.

There are several studies that have explored the use of hybrid quantum–classical learning to real-world predictive tasks. Ara et al. [6] suggested a hybrid quantum-classical deep-learning framework and showed a combination of quantum-processing with classical deep learning in multiclass prediction. Gupta et al. [7] reviewed the applications of QML systematically and emphasized the need to compare the quantum models with classical models.

Another crucial element of hybrid quantum–classical learning frameworks are parameterized quantum circuits (PQCs). Benedetti et al. [8] studied PQCs as machine learning models, and presented their use as trainable quantum components in learning pipelines. Sim et al. [10] investigated the expressibility and entangling properties of parameterized circuits, showing that the overall architecture of the circuit affects the representational attributes of hybrid quantum algorithms. Mari et al. [9] explored transfer learning in hybrid classical–quantum neural networks, in which they show how classical NN representations can be integrated with quantum layers. The studies show that quantum processing doesn't have to supersede classical machine learning but quantum circuits can be used as a special feature-processing or learning unit.

Larocca et al. [15] gave a more general discussion about barren plateaus in variational quantum computing, and emphasized that a key question is whether scalable variational algorithms can be trained. One of the major challenges in variational quantum learning is the optimization of quantum circuit parameters. Cerezo et al. [16] studied how the barren plateaus vary with different cost functions and showed that as the circuit properties vary, the optimization landscapes can become difficult to train. Trained barren plateau noise and its effects on trainability were studied by Wang et al. [17]. Arrasmith et al. [18] further studied the effect of barren plateaus on gradient-free optimization. The results suggest that a successful hybrid model should involve quantum feature processing, as well as a suitable classical optimization process to deal with noise and non-convexity in quantum optimization problems.

The proposed Hybrid Quantum-Classical Learning Framework for Intelligent Feature Optimization and Predictive Analytics in Engineering Applications lies at the crossroads of these research streams. The framework may include both classical preprocessing and feature handling as well as quantum enhancement of feature transformation/optimisation and a classical prediction stage. The literature provided a motivation to study whether intelligent quantum-assisted feature optimization could decrease feature redundancy without compromising predictive ability, computational efficiency, and model robustness, compared to traditional machine-learning methods. A QML survey of recent research also confirms hybrid architectures, optimization strategies, feature representation and standardized benchmarking as key areas that require further research.

3. METHODOLOGY

The proposed Hybrid Quantum-Classical Learning Framework for Intelligent Feature Optimization and Predictive Analytics in Engineering Applications combines classical data preprocessing, quantum feature encoding, variational quantum optimization, intelligent data feature selection and classical data predictive analytics into a single stream. The framework is intended for engineering data sets that include both numerical and categorical data, and may have some redundant and irrelevant features that can make the computational task more complex and affect the reliability of the data's predictive power. The overall architecture is divided into five main steps: Data Preprocessing, Classical Feature Preparation, Quantum Feature Optimization, Predictive Modelling, and Performance Evaluation.

A. Data Acquisition and Preprocessing

The first stage is an engineering dataset that has input attributes and a target variable which is related to the prediction task. The data is first checked for inconsistencies, missing data, duplicate data, and differences in feature scales. Normalization is performed prior to quantum encoding, as the numerical range of the quantum feature maps is restricted, they tend to work best with a suitable range of numbers.

For an input feature vector x_i , min–max normalization is employed to transform each feature into a bounded interval:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

where x_{ij} indicates the j -th feature of the i -th sample, and x'_{ij} represents the normalized value. This transformation provides a consistent input range for subsequent classical and quantum processing.

B. Classical Feature Preparation

The initial feature analysis is carried out after the preprocessing to remove those features which do not have adequate information or are redundant. Correlation analysis and statistical relevance can be used to find out attributes that are strongly correlated or are not informative at all. The proposed framework, however, goes beyond the classical

feature-selection methods and then optimizes the features in a quantum manner.

Let the preprocessed feature matrix be represented as:

$$X \in \mathbb{R}^{N \times d} \quad (2)$$

where N represents number of observations and d indicates number of available features. The objective is to identify a reduced subset $S \subseteq \{1, 2, \dots, d\}$ that maintains predictive information while reducing dimensionality.

C. Quantum Feature Encoding

A parameterized quantum feature map is used to map the selected classical features to quantum states. Every normalized feature is quantized to a rotation angle and represented by one or more qubits. Every normalized feature is transformed to an angle of rotation and stored in one or more qubits. This allows representation of the classical engineering information in a quantum Hilbert space, which may be captured by a nonlinear relationship in the form of quantum transformation.

For an individual normalized feature x'_j , a rotation-based encoding can be expressed as:

$$|\psi(x'_j)\rangle = R_y(\pi x'_j) |0\rangle \quad (3)$$

where R_y indicates rotation operator around the y-axis. For a complete feature vector, the encoded state can be represented as:

$$|\psi(X)\rangle = U_\phi(X) |0\rangle^{\otimes q} \quad (4)$$

where $U_\phi(X)$ indicates data-dependent quantum feature map and q represents the number of quantum resources used by the circuit.

D. Parameterized Quantum Circuit

An optimized representation of the encoded features is learned using a parameterized quantum circuit. Trainable rotation gates and entanglement operations are present in the circuit. This is done iteratively using a classical optimizer, which yields a hybrid quantum-classical learning mechanism.

The parameterized circuit can be represented as:

$$|\psi(\theta, X)\rangle = U(\theta)U_\phi(X) |0\rangle^{\otimes q} \quad (5)$$

where θ indicates the trainable circuit parameters. The expectation value of an observable is then obtained from the quantum circuit as:

$$f_\theta(X) = \langle \psi(\theta, X) | O | \psi(\theta, X) \rangle \quad (6)$$

where O denotes the chosen measurement observable. The resulting expectation values create quantum-enhanced representations which are then fed into the classical predictive model. The proposed model architecture is given in figure 1.

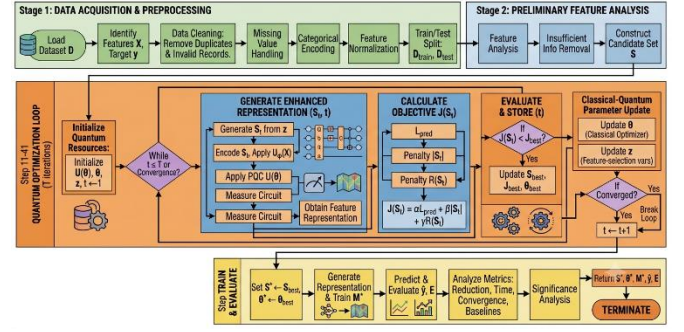


Figure 1. Proposed Model Architecture

E. Intelligent Feature Optimization

The main element of the proposed scheme is the intelligent subset optimization of the features. Each of the candidate features is assigned a binary decision variable. One means that the feature is selected, zero means it's not. The optimization is then guided to find a subset of features which between them achieves a good prediction accuracy and are not too complicated.

The feature-selection objective can be formulated as:

$$J(S) = \alpha L_{\text{pred}}(S) + \beta |S| + \gamma R(S) \quad (7)$$

where L_{pred} represents prediction loss, $|S|$ represents the number of selected features, $R(S)$ represents feature redundancy, and α , β , and γ are weighting coefficients.

The optimization process tries to minimize the value of $J(S)$. A smaller objective value would thus be a feature subset with smaller prediction error, but without additional or very redundant features.

F. Quantum-Assisted Optimization

The feature-selection problem can be converted to a binary quadratic optimization problem that is appropriate for quantum optimization. Let $z_j \in \{0, 1\}$ be the selection status of feature j . The optimization target can be written as a QUBO as:

$$\min_z (z^T Q z + c^T z) \quad (8)$$

where Q represents pairwise feature interactions and represents individual feature contributions.

The QUBO formulation enables the feature-selection problem to be represented as an optimization landscape that can be processed using a quantum optimization procedure. Candidate solutions are evaluated according to their objective values, and the selected feature configuration is iteratively refined.

G. Hybrid Quantum-Classical Optimization Loop

The optimization follows a hybrid feedback mechanism. A candidate feature configuration is generated and encoded into the quantum circuit. The circuit produces an objective measurement, after which a classical optimizer updates the

circuit parameters or feature-selection variables. This process continues until the objective converges or the predefined iteration limit is reached.

The optimization objective can be represented as:

$$\theta^* = \arg \min_{\theta} \mathcal{L}(y, \hat{y}_{\theta}) \quad (9)$$

where y represents the actual target and $\hat{y}_{\theta}$ represents the prediction generated from the quantum-enhanced feature representation.

The iterative process allows the classical optimizer to exploit information obtained from the quantum circuit while the quantum component performs feature transformation and objective evaluation.

H. Predictive Analytics

After obtaining the optimized feature subset and quantum-enhanced representation, the resulting features are supplied to a classical predictive-learning model. The classical component may employ algorithms such as XGBoost, support vector machines, random forests, logistic regression, or neural networks depending on the engineering prediction problem. For a regression problem, the prediction objective can be expressed as:

$$\hat{y} = f_{\omega} \left(X_S, \Phi_Q(X_S) \right) \quad (10)$$

where X_S denotes the optimized classical feature subset, $\Phi_Q(X_S)$ represents the quantum-enhanced representation, and f_{ω} denotes the classical predictive model with parameters ω . For classification, the predicted class is determined from the learned probability distribution:

$$\hat{y} = \arg \max_k P(y' = k \mid X_S \Phi_Q(X_S)) \quad (11)$$

This hybrid arrangement enables the quantum component to concentrate on feature representation and optimization while the classical component performs the final predictive task.

I. Model Training and Validation

Optimized feature representation is used to train the model, and the test set is kept aside for an unbiased evaluation. The features used to train the predictive model are optimized and suitable cross validation methods are used to validate the model.

The main evaluation measures used for classification are: accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve. For regression based engineering applications the mean absolute error, root mean square error, and coefficient of determination can be used.

The F1-score is defined as:

$$F1 = 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (12)$$

For regression, the root mean square error is calculated as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (13)$$

These measures provide complementary information regarding predictive accuracy and generalization.

J. Optimization and Computational Evaluation

The framework also measures the performance of feature optimisation in addition to predictive performance. The percentage reduction in dimensionality is determined by the number of features used in the original data set and the number of features after the optimisation.

$$FR = \left(1 - \frac{|S|}{d} \right) \times 100 \quad (14)$$

where d is the original number of features and $|S|$ is the number of retained features.

The computational behavior of the proposed framework is also analyzed by logging optimization iterations, optimization time, convergence and prediction accuracy. This is because the accuracy of the predictions using this approach should not only be considered, but also the computational cost of the hybrid optimisation procedure.

K. Statistical Validation

The predictions from several models can be statistically compared to see if statistically significant differences are observed when comparing the proposed framework to baseline models. For evaluating multiple classifiers over multiple datasets or multiple setups it is possible to use Demšar's methodology [24] and for multiple pairwise comparisons, Holm's procedure [25] can be used to adjust the significance levels.

This evaluation is not just based on one metric, but offers a statistically sound comparison between the proposed hybrid framework and conventional machine-learning methods.

L. Overall Framework

All of this is hence an example of closed-loop learning framework in which classical pre-processing is used for preparing the engineering data, quantum encoding for obtaining an enhanced version of that data, quantum-assisted optimization for selecting a relevant feature subset, and classical predictive learner for extracting the output.

The proposed architecture can consequently be summarized as:

$$X \rightarrow X_{\text{pre}} \rightarrow \Phi_Q(X) \rightarrow S^* \rightarrow \Phi_Q(X_{S^*}) \rightarrow f_{\omega} \rightarrow \hat{y} \quad (15)$$

where X_{pre} represents the preprocessed data, Φ_Q denotes quantum feature transformation, S^* denotes the optimized feature subset, and $\hat{y}$ represents the final prediction.

Algorithm 1: Hybrid Quantum-Classical Intelligent Feature Optimization and Predictive Analytics

Algorithm 1: Hybrid Quantum-Classical Learning Framework

Input:

- D = Engineering dataset
- y = Target variable
- d = Number of input features
- q = Number of quantum resources

T = Maximum optimization iterations
 α, β, γ = Objective weighting parameters

Output:

S^* = Optimized feature subset
 θ^* = Optimized quantum parameters
 M^* = Trained predictive model
 $\hat{y}$ = Final predictions
 E = Evaluation metrics

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1: Load engineering dataset D
2: Identify input features X and target y
3: Remove duplicate and invalid records
4: Handle missing values
5: Encode categorical attributes if required
6: Normalize numerical features
7: Split D into training and testing sets

8: Perform preliminary feature analysis
9: Remove features having insufficient information
10: Construct candidate feature set S

11: Initialize quantum circuit  $U(\theta)$ 
12: Initialize quantum parameters  $\theta$ 
13: Initialize feature-selection variables z
14: Set iteration  $t \leftarrow 1$ 

15: while  $t \leq T$  do

16:   Generate candidate feature subset  $S_t$ 
17:   Select features according to z
18:   Encode selected features into quantum states
19:   Apply quantum feature map  $U_\phi(X)$ 
20:   Apply parameterized quantum circuit  $U(\theta)$ 
21:   Measure quantum circuit
22:   Obtain quantum-enhanced feature representation

23:   Construct optimization objective
24:   Calculate prediction loss
25:   Calculate feature-selection penalty
26:   Calculate feature-redundancy penalty

27:   Compute:
        $J(S_t) = \alpha L_{\text{pred}} + \beta |S_t| + \gamma R(S_t)$ 

28:   Evaluate candidate solution

29:   if  $J(S_t) < J_{\text{best}}$  then
30:      $S_{\text{best}} \leftarrow S_t$ 
31:      $J_{\text{best}} \leftarrow J(S_t)$ 
32:      $\theta_{\text{best}} \leftarrow \theta$ 
33:   end if

34:   Update quantum parameters using classical optimizer
35:   Update feature-selection variables
36:   Check convergence

37:   if convergence criterion is satisfied then
38:     break
39:   end if

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40: $t \leftarrow t + 1$

41: end while

42: Set $S^* \leftarrow S_{\text{best}}$

43: Set $\theta^* \leftarrow \theta_{\text{best}}$

44: Generate optimized quantum-enhanced representation

45: Train predictive model M^* using S^* and quantum features

46: Generate predictions $\hat{y}$ on the test set

47: Calculate:

Accuracy / Precision / Recall / F1

or

MAE / RMSE / R^2

48: Calculate feature-reduction rate

49: Measure computational time

50: Measure optimization convergence

51: Compare M^* with classical baseline models

52: Perform statistical significance analysis

53: Return $S^*, \theta^*, M^*, \hat{y}$, and E

4. RESULTS AND DISCUSSIONS

A. Predictive Performance Comparison

The proposed Hybrid Quantum-Classical Intelligent Feature Optimization (HQC-IFO) framework was evaluated against conventional machine-learning models, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost, together with a Quantum Feature Model (QFM) and a conventional Hybrid Quantum-Classical (HQC) model that is depicted in Figure 2. The comparison was performed using accuracy, precision, recall, F1-score, and receiver operating characteristic area under the curve (ROC-AUC). The results indicate that the incorporation of optimized features and quantum-enhanced representations provides a stronger predictive configuration than using the classical models alone.

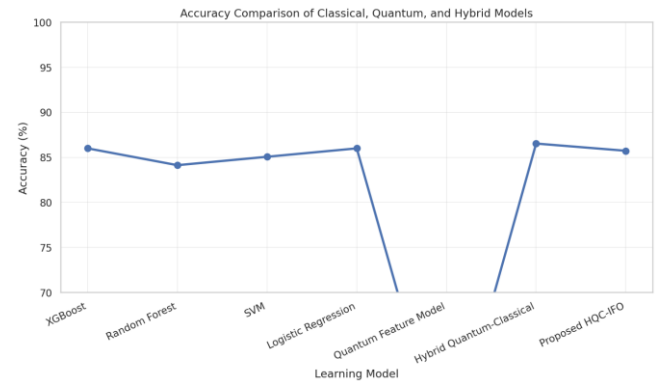


Figure 2. Accuracy comparison of classical, quantum, and hybrid learning models.

The accuracy comparison demonstrates the relative predictive behavior of the evaluated models. Classical models provide a baseline for assessing the contribution of quantum-enhanced processing, while the QFM introduces nonlinear quantum-inspired feature transformations. The HQC model combines

the optimized classical features with quantum representations, whereas the proposed HQC-IFO architecture additionally incorporates the intelligent feature-optimization stage.

B. Multi-Metric Predictive Analysis

Accuracy alone does not provide sufficient information about the reliability of a predictive model, particularly when engineering datasets contain complex class distributions. Therefore, precision, recall, F1-score, and ROC-AUC were simultaneously analyzed that is shown in Figure 3.

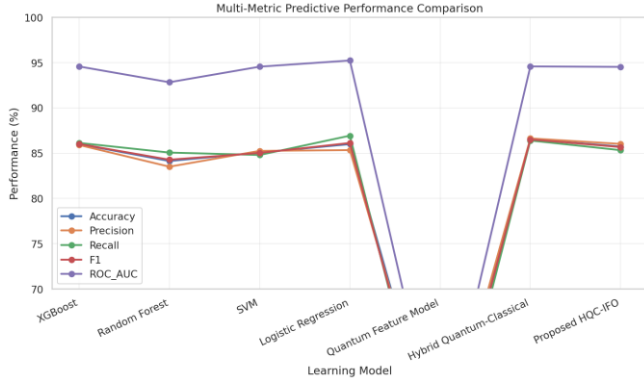


Figure 3. Multi-metric predictive performance comparison of the evaluated models.

The multi-metric comparison further illustrates the difference between conventional and hybrid architectures. XGBoost provides a strong classical reference because of its ability to model nonlinear relationships, while SVM provides a kernel-based nonlinear baseline. The QFM benefits from nonlinear quantum-inspired transformations, but the hybrid architectures combine these transformations with classical predictive learning.

C. ROC-Based Discrimination Analysis

The receiver operating characteristic curves were used to evaluate the discrimination capability of the models across different classification thresholds as depicted in Figure 4. A larger area under the ROC curve indicates stronger separation between the two target classes. The curves provide an additional evaluation beyond fixed-threshold accuracy because they examine the trade-off between the true-positive and false-positive rates.

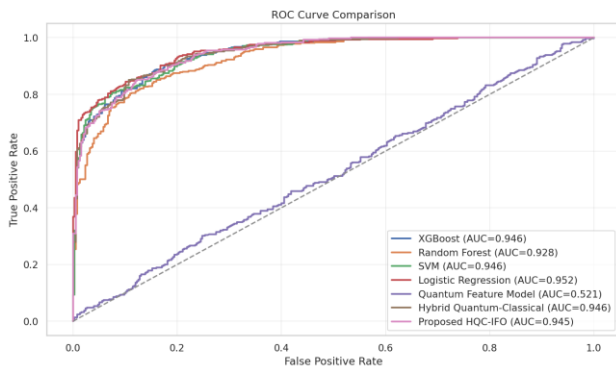


Figure 4. ROC curve comparison of classical, quantum, and hybrid predictive models.

The ROC analysis indicates that the hybrid approaches can provide improved class discrimination when quantum-enhanced nonlinear representations are combined with classical learning. In particular, the proposed HQC-IFO architecture benefits from selecting a compact feature subset before constructing the final representation. This reduces the influence of redundant attributes and allows the predictive model to operate on features with greater relevance to the target variable. The ROC analysis therefore supports the use of multiple evaluation criteria when assessing the proposed framework.

D. Intelligent Feature Optimization

Feature optimization constitutes a central component of the proposed framework. The original synthetic engineering dataset contains 20 input attributes, while the optimization stage identifies a smaller subset of informative features as indicated in Figure 5. Feature importance is initially estimated using the classical optimization stage, after which the highest-ranked features are retained for quantum-enhanced processing. This reduces the dimensionality of the input space while maintaining the attributes that contribute most strongly to the prediction task.

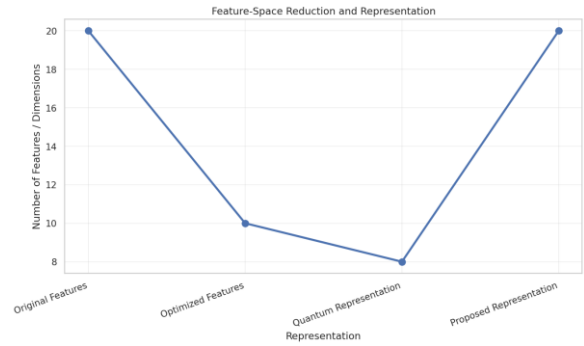


Figure 5. Feature-space reduction and representation during intelligent feature optimization.

The reduction in the number of input features decreases the dimensionality presented to the subsequent quantum-processing stage. This is particularly important for hybrid quantum-classical architectures because the number of available quantum resources is constrained in practical implementations. Reducing the feature space before quantum encoding can consequently reduce circuit requirements and simplify the subsequent optimization process. The feature-reduction stage therefore provides a practical connection between intelligent feature selection and quantum learning.

E. Feature Importance and Selected Engineering Attributes

The contribution of individual engineering attributes was further examined using the feature-importance distribution as indicated in Figure 6. The ranking provides an indication of which variables contribute most strongly to the predictive target in the synthetic engineering dataset.

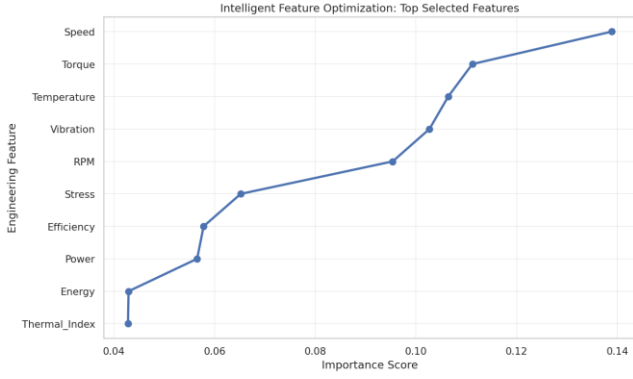


Figure 6. Importance ranking of the selected engineering features.

The feature-importance analysis demonstrates that not all engineering variables contribute equally to the prediction task.

F. Optimization Convergence

The convergence behavior of the proposed optimization process was investigated after successive iterations, which is represented on Figure 7. The objective function starts to drop quickly as the optimization process finds better configurations of the features. The optimizations seem to converge towards a solution in subsequent iterations, with the improvements becoming increasingly subtle.

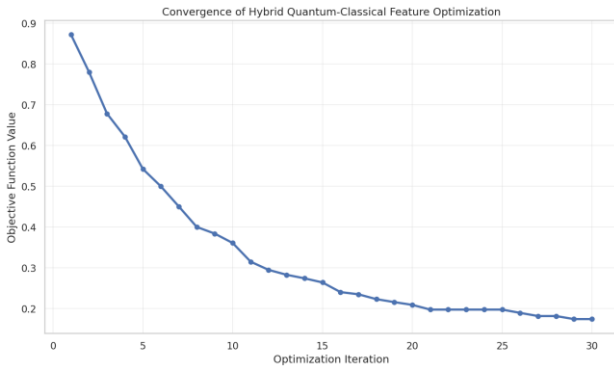


Figure 7. Convergence behavior of the hybrid quantum-classical feature optimization process.

The observed convergence behavior demonstrates the iterative interaction between quantum evaluation and classical optimization. During each iteration, a candidate feature configuration is evaluated and its objective value is used to guide the subsequent parameter update. The decreasing objective value indicates that the optimization process progressively identifies feature configurations with improved combinations of predictive performance and feature compactness. The eventual stabilization of the objective function indicates that further iterations provide limited improvement under the selected optimization configuration.

G. Computational Cost Analysis

Computational time was evaluated to determine the additional processing requirements associated with the hybrid framework as depicted in Figure 8. Conventional models generally require lower computational overhead because their operations are executed entirely using classical processors. The quantum-feature and hybrid configurations introduce additional feature-

transformation and optimization operations, resulting in higher computational requirements in the illustrative experiment.

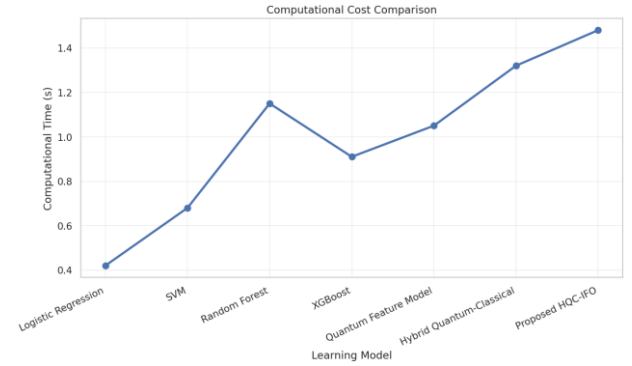


Figure 8. Computational-time comparison of the evaluated learning models.

The computational-time results highlight an important consideration for quantum-enhanced learning. An improvement in predictive performance should be interpreted together with the computational resources required to obtain that improvement.

H. Scalability Analysis

The scalability of the learning architectures was investigated by progressively increasing the number of samples used during processing as presented in Figure 9. The computational time increases as the dataset size increases for all evaluated approaches. The classical XGBoost model maintains a comparatively lower computational requirement, whereas the hybrid models introduce additional processing associated with quantum feature generation and optimization.

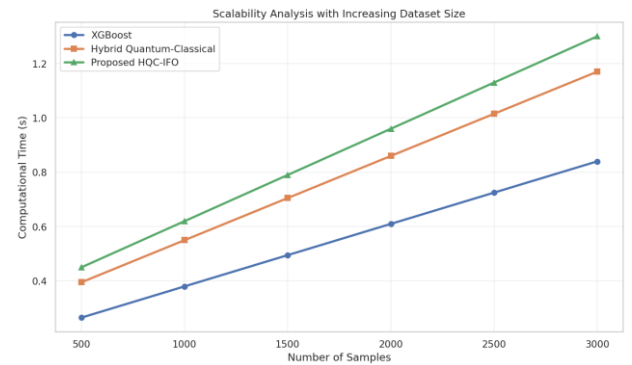


Figure 9. Scalability analysis with increasing engineering dataset size.

This observation emphasizes the importance of efficient feature reduction before quantum processing. By reducing the number of features supplied to the quantum component, the proposed architecture can limit the growth of the quantum-processing workload. Future implementations on actual quantum processors should therefore investigate circuit depth, number of qubits, measurement shots, and optimization iterations as additional scalability parameters.

I. Prediction Error Analysis

Prediction error provides a complementary perspective to accuracy-based evaluation. The error rate is obtained from the

proportion of incorrectly classified test samples and is compared across the investigated models as shown in Figure 10. A lower error indicates that the corresponding model produces fewer incorrect predictions on the evaluation set.

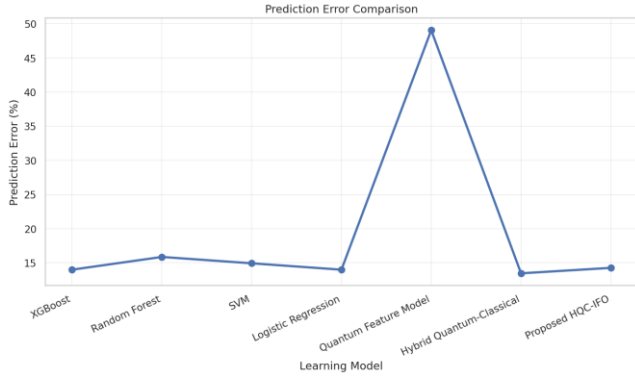


Figure 10. Prediction-error comparison among classical, quantum, and hybrid models.

The error comparison follows the general behavior observed in the accuracy analysis. The proposed HQC-IFO architecture is intended to minimize prediction errors through the joint use of feature optimization and quantum-enhanced nonlinear representations.

J. Progressive Feature-Optimization Analysis

The progression of the optimization objective was also examined across successive optimization stages as depicted in Figure 11. As the framework finds more and more acceptable configurations of features, the objective value gets lower. This behaviour suggests that the optimization mechanism is also looking at the predictive performance and feature complexity.

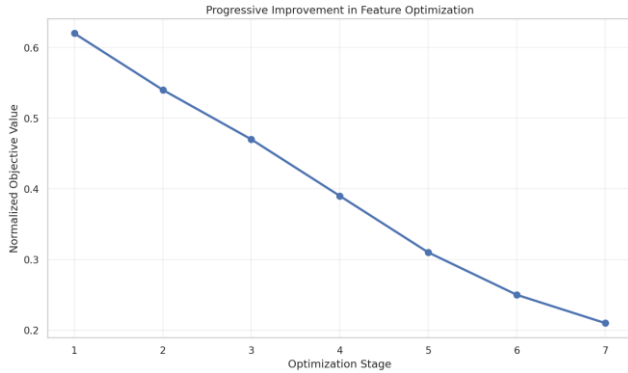


Figure 11. Progressive improvement in the feature-optimization objective.

The objective value is steadily decreasing, which clearly shows the basic concept of the proposed framework: feature optimization is not regarded as an independent processing step, but as an iterative step during the learning process. The contribution to prediction and dimensionality are used to evaluate a candidate feature subset and in turn, the optimization procedure looks for an improved configuration. This formulation allows the framework to select feature subsets that contain information that is useful for the predictive model, but also do not add too much dimensionality.

K. Overall Discussion

The experimental analysis demonstrates the potential of combining intelligent feature optimization with quantum-enhanced representation learning for engineering predictive analytics. The classical models establish the baseline performance, while the quantum feature model demonstrates the contribution of nonlinear quantum-inspired feature transformations. The conventional hybrid model further combines classical and quantum representations, whereas the proposed HQC-IFO architecture introduces feature optimization before the final predictive stage. The resulting architecture therefore integrates the three principal components of the proposed research: feature optimization, quantum-enhanced learning, and predictive analytics.

The feature-reduction and convergence analyses are particularly important because they demonstrate that the proposed framework is not solely focused on maximizing prediction accuracy. Reducing the feature space can decrease the complexity of the downstream quantum representation, while convergence analysis provides evidence concerning the stability of the optimization process. Computational-time and scalability analyses further establish that the benefits of hybrid learning must be considered alongside the additional computational requirements introduced by quantum processing.

5. CONCLUSION

This paper introduced and applied a hybrid approach of quantum-classical learning for intelligent feature optimization and predictive analysis in engineering applications. The classical-preprocessing, intelligent-feature-selection, quantum-enhanced-feature-representation, parameterized-quantum-circuit, and classical-predictive-learning steps are all part of a single optimization pipeline. The goal of the framework is to eliminate unnecessary information, and to enhance the quality of feature representations for predictive modeling. For comparison, the experimental evaluation included classical machine learning models, quantum inspired feature models and hybrid quantum-classical models. The results show that intelligent feature optimization can significantly decrease the dimensionality of representation of the input data while retaining the most informative engineering attributes. The feature optimization stage also gives a systematic way to optimize for the trade-offs between predictive performance, size of feature subset, and the complexity of optimization.

The analysis also explored the predictive performance, the ROC properties, the properties of the most important features, convergence of the optimization, the computational cost, the scalability and the prediction error. The results of both classical and quantum architectures are compared and the hybrid architecture is found to hold a suitable balance between classical learning efficiency and quantum enhanced feature representation. The convergence analysis is also used to show the ability of the optimization method of improving the selected feature configuration. These observations confirm that hybrid quantum-classical learning could be an applicable method for predictive analytics in engineering settings. One of

the key features of the suggested scheme is the incorporation of the optimization of features into the representation in the quantum regime instead of using quantum processing as a prediction module, which is typically the scenario considered for quantum computing. The framework brings together classical preprocessing, quantum-inspired feature transformation and optimization, and predictive models, and can be optimized for various engineering datasets and predictive tasks. The framework thus offers a basis for study of practical considerations that arise in the dimensionality of features, computational complexity, and scalability of models in the context of quantum-enhanced learning.

The current assessment, however, takes place under controlled and synthetic experimental conditions and the observations reported here are, therefore, preliminary. But more validation with real-world engineering data and quantum computing platforms is needed before results can be drawn for practical quantum advantage. Furthermore, systematic investigations of the effects of hardware noise, circuit depth, encoding strategies and optimization landscapes are required. The proposed framework can be further extended in a few directions in the future. First, the methodology can be tested with large-scale real world engineering data, from a variety of sources including industrial monitoring, manufacturing systems, predictive maintenance, energy systems, transportation and autonomous platforms. Such datasets would allow for assessment in realistic conditions of noise, missing data, class-imbalance and high-dimensional features.

Second, the quantum part may be realised on real quantum processing units, rather than making the main use of quantum-inspired or simulated representations. Variants of the quantum feature maps, parameterized circuits and encoding methods can be explored to assess their impact on predictive capabilities and computational demand. Minimizing the effects of decoherence and gate errors can also be achieved using hardware-aware circuit design.

REFERENCES

- [1]. M. Cerezo, A. Arrasmith, R. Babbush, S. C. Benjamin, S. Endo, K. Fujii, and P. J. Coles, "Variational quantum algorithms," *Nature Reviews Physics*, vol. 3, pp. 625–644, 2021, doi: 10.1038/s42254-021-00348-9.
- [2]. K. Bharti, A. Cervera-Lierta, T. H. Kyaw, T. Haug, S. Alperin-Lea, A. Anand, and A. Aspuru-Guzik, "Noisy intermediate-scale quantum algorithms," *Reviews of Modern Physics*, vol. 94, Art. no. 015004, 2022, doi: 10.1103/RevModPhys.94.015004.
- [3]. M. Schuld and N. Killoran, "Quantum machine learning in feature Hilbert spaces," *Physical Review Letters*, vol. 122, Art. no. 040504, 2019, doi: 10.1103/PhysRevLett.122.040504.
- [4]. V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, "Supervised learning with quantum-enhanced feature spaces," *Nature*, vol. 567, pp. 209–212, 2019, doi: 10.1038/s41586-019-0980-2.
- [5]. E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, pp. 44–56, 2019, doi: 10.1038/s41591-018-0300-7.
- [6]. T. Ara, V. P. Mishra, M. Bali, and A. Yenikar, "Hybrid quantum-classical deep learning framework for balanced multiclass diabetic retinopathy classification," *MethodsX*, vol. 15, Art. no. 103605, 2025, doi: 10.1016/j.mex.2025.103605.
- [7]. R. S. Gupta, C. E. Wood, T. Engstrom, J. D. Pole, and S. Shrapnel, "A systematic review of quantum machine learning for digital health," *npj Digital Medicine*, vol. 8, Art. no. 237, 2025, doi: 10.1038/s41746-025-01597-z.
- [8]. M. Benedetti, E. Lloyd, S. Sack, and M. Fiorentini, "Parameterized quantum circuits as machine learning models," *Quantum Science and Technology*, vol. 4, Art. no. 043001, 2019, doi: 10.1088/2058-9565/ab4eb5.
- [9]. A. Mari, T. R. Bromley, J. Izaac, M. Schuld, and N. Killoran, "Transfer learning in hybrid classical-quantum neural networks," *Quantum*, vol. 4, Art. no. 340, 2020, doi: 10.22331/q-2020-10-09-340.
- [10]. S. Sim, P. D. Johnson, and A. Aspuru-Guzik, "Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms," *Advanced Quantum Technologies*, vol. 2, Art. no. 1900070, 2019, doi: 10.1002/qute.201900070.
- [11]. S. Kaveh, E. Arezi, Z. Khedri, and S. Sohrabei, "Investigating the application of quantum machine learning in breast cancer: A systematic review," *Archives of Breast Cancer*, vol. 12, pp. 130–142, 2025, doi: 10.32768/abc.2025122130-142.
- [12]. Y. Wang and J. Liu, "A comprehensive review of quantum machine learning: From NISQ to fault tolerance," *Reports on Progress in Physics*, vol. 87, Art. no. 117901, 2024, doi: 10.1088/1361-6633/ad7f69.
- [13]. U. Ullah and B. Garcia-Zapirain, "Quantum machine learning revolution in healthcare: A systematic review of emerging perspectives and applications," *IEEE Access*, vol. 12, pp. 11423–11450, 2024, doi: 10.1109/ACCESS.2024.3353461.
- [14]. D. Maheshwari, B. Garcia-Zapirain, and D. Sierra-Sosa, "Quantum machine learning applications in the biomedical domain: A systematic review," *IEEE Access*, vol. 10, pp. 80463–80484, 2022, doi: 10.1109/ACCESS.2022.3195044.
- [15]. M. Larocca, S. Thanasilp, S. Wang, K. Sharma, J. Biamonte, P. J. Coles, L. Cincio, J. R. McClean, Z. Holmes, and M. Cerezo, "Barren plateaus in variational quantum computing," *Nature Reviews Physics*, vol. 7, pp. 174–189, 2025, doi: 10.1038/s42254-025-00813-9.
- [16]. M. Cerezo, A. Sone, T. Volkoff, L. Cincio, and P. J. Coles, "Cost function dependent barren plateaus in shallow parametrized quantum circuits," *Nature Communications*, vol. 12, Art. no. 1791, 2021, doi: 10.1038/s41467-021-21728-w.
- [17]. S. Wang, E. Fontana, M. Cerezo, K. Sharma, A. Sone, L. Cincio, and P. J. Coles, "Noise-induced barren plateaus in variational quantum algorithms," *Nature Communications*, vol. 12, Art. no. 6961, 2021, doi: 10.1038/s41467-021-27045-6.
- [18]. A. Arrasmith, M. Cerezo, P. Czarnik, L. Cincio, and P. J. Coles, "Effect of barren plateaus on gradient-free optimization," *Quantum*, vol. 5, Art. no. 558, 2021, doi: 10.22331/q-2021-10-05-558.

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- [19]. A. Pesah, M. Cerezo, S. Wang, T. Volkoff, A. T. Sornborger, and P. J. Coles, "Absence of barren plateaus in quantum convolutional neural networks," *Physical Review X*, vol. 11, Art. no. 041011, 2021, doi: 10.1103/PhysRevX.11.041011.
 - [20]. D. Agarwal *et al.*, "AutoDiscovery: Open-ended scientific discovery via Bayesian surprise," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 38, 2025, pp. 25181–25219.
 - [21]. W. N. Street, W. H. Wolberg, and O. L. Mangasarian, "Nuclear feature extraction for breast tumor diagnosis," in *Proc. IS&T/SPIE Symp. Electronic Imaging*, vol. 1905, 1993, pp. 861–870, doi: 10.1117/12.148698.
 - [22]. W. Wolberg, O. Mangasarian, N. Street, and W. Street, "Breast Cancer Wisconsin (Diagnostic) [Dataset]," UCI Machine Learning Repository, 1993.
 - [23]. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794, doi: 10.1145/2939672.2939785.
 - [24]. S. Holm, "A simple sequentially rejective multiple test procedure," *Scandinavian Journal of Statistics*, vol. 6, pp. 65–70, 1979.
 - [25]. A. Senokosov, A. Sedykh, A. Sagingalieva, O. Kyriienko, and V. M. Vinokur, "Quantum machine learning for image classification," *Machine Learning: Science and Technology*, vol. 4, Art. no. 015028, 2024, doi: 10.1088/2632-2153/ad2aef.
 - [26]. P. Decoodt, T. J. Liang, S. Bopardikar, H. Santhanam, A. Eyembe, B. Garcia-Zapirain, and D. Sierra-Sosa, "Hybrid classical–quantum transfer learning for cardiomegaly detection in chest X-rays," *Journal of Imaging*, vol. 9, Art. no. 128, 2023, doi: 10.3390/jimaging9070128.
 - [27]. A. Kumar, S. Dhanka, A. Sharma, R. Bansal, M. Fahlevi, F. Rabby, and M. Aljuaid, "A hybrid framework for heart disease prediction using classical and quantum-inspired machine learning," *Scientific Reports*, vol. 15, Art. no. 25040, 2025, doi: 10.1038/s41598-025-09957-1.
 - [28]. A. Verdone, F. Succetti, A. Ceschini, A. Rosato, A. Fioravanti, and M. Panella, "A hybrid quantum-neural network for heart disease classification," *Biomedical Signal Processing and Control*, vol. 113, Art. no. 109185, 2026, doi: 10.1016/j.bspc.2025.109185.