A
Project Report
On

Quantum Machine Learning-Assisted Support Vector Machines for Improved Cancer Prediction

Submitted in partial fulfillment of
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BACHELOR OF TECHNOLOGY
IN

Computer Science and Engineering

By

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CERTIFICATE

This is to certify that the project work entitled "Quantum Machine Learning-Assisted Support Vector Machines for Improved Cancer Prediction" is done by Sritesh Kumar Bisi (21UG010650), Aryan Behera (21UG010192) in partial fulfillment of the requirements for the 8th Semester Sessional Examination of Bachelor of Technology in Computer Science and Engineering during the academic year 2024-25. This work is submitted to the department as a part of evaluation of 8th Semester Major Project-II.

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CANDIDATES DECLARATION

We hereby declare that the work which is being presented in the thesis entitled "Quantum Machine Learning-Assisted Support Vector Machines for Improved Cancer Prediction" by **Sritesh Kumar Bisi(21UG010650), Aryan Behera(21UG010192)**in partial fulfillment of requirements for the award of degree of B.Tech. CSE submitted in the Department of CSE under GIET UNIVERSITY, GUNUPUR, India is an authentic record of my own work carried out during a period from **December 2025 to April 2025** under the supervision of **Dr. Sachikanta Dash**. The matter presented in this thesis has not been submitted by me in any other University / Institute for the award of B.Tech Degree.

This is to certify that the above statement made by us is correct to the best of our knowledge.

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ABSTRACT

Quantum Machine Learning (QML) is an emerging field that leverages quantum computing principles, such as superposition and entanglement, to enhance computational efficiency in machine learning tasks. This study explores recent advancements in QML applications, focusing on healthcare diagnostics, fraud detection, and quantum kernel-based classification. In healthcare, QML models such as Quantum Support Vector Machines (QSVM), Variational Quantum Classifiers (VQC), and Quantum Neural Networks (QNN) have demonstrated potential in improving disease classification and medical imaging analysis. However, challenges such as qubit decoherence and hardware limitations remain significant barriers. In fraud detection, hybrid quantum-classical approaches utilizing quantum feature selection and quantum annealing have shown promising results in handling imbalanced datasets and optimizing financial security systems. Additionally, benchmarking studies on quantum kernel training highlight the advantages and limitations of QML in classification tasks, emphasizing the importance of quantum feature map selection. Despite current hardware constraints, hybrid QML architectures present a feasible path toward integrating quantum computing into practical machine learning applications. This research aims to provide a comprehensive analysis of the potential and challenges associated with QML, offering insights into its future trajectory.

Keywords:

Quantum Machine Learning (QML), Quantum Support Vector Machine (QSVM), Variational Quantum Classifier (VQC), Quantum Neural Networks (QNN), Quantum Kernel Training (QKT), Fraud Detection, Hybrid Quantum-Classical Models, Medical Imaging, Quantum Feature Selection, Quantum Annealing.

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INTRODUCTION

Quantum computing has emerged as a revolutionary paradigm with the potential to redefine classical computing limitations. One of the most promising areas of quantum computing is Quantum Machine Learning (QML), which integrates quantum principles such as superposition, entanglement, and quantum parallelism to enhance machine learning models. Traditional machine learning methods often struggle with computational inefficiencies, particularly when dealing with high-dimensional data and complex optimization tasks. QML offers a potential solution by leveraging quantum mechanics to process vast amounts of data more efficiently than classical algorithms.

1.1 Motivation and Significance:

Recent advancements in quantum hardware and algorithms have spurred interest in QML applications across various domains, including healthcare, fraud detection, and artificial intelligence. In healthcare, QML models such as Quantum Support Vector Machines (QSVM), Variational Quantum Classifiers (VQC), and Quantum Neural Networks (QNN) have demonstrated promising results in medical diagnostics, particularly in image classification tasks such as skin lesion analysis and breast cancer detection. The ability of quantum-enhanced models to analyze large-scale, high-dimensional datasets makes them a compelling alternative to classical machine learning approaches. However, current hardware limitations, including qubit decoherence, noise, and scalability challenges, pose significant barriers to real-world deployment. Similarly, in fraud detection, QML has shown potential in identifying fraudulent transactions in financial systems. Hybrid quantum-classical models that integrate quantum feature selection and kernel-based classification have been developed to enhance the accuracy of fraud detection systems. Quantum-enhanced optimization techniques such as quantum annealing further improve computational efficiency, particularly in handling imbalanced datasets—one of the primary challenges in financial fraud detection.

1.2 Challenges:

Despite the theoretical advantages of QML, its practical application remains constrained by the current state of quantum hardware. Issues such as **limited qubit coherence times,**

gate errors, and the need for specialized quantum hardware hinder the seamless transition from theoretical models to real-world implementations. Additionally, while certain QML approaches demonstrate superior performance on quantum-friendly datasets, they often fail to generalize across diverse real-world problems. This research aims to explore the feasibility, advantages, and limitations of QML models in real-world applications, particularly in healthcare diagnostics and fraud detection. The study will investigate various QML architectures, including quantum kernel methods, variational circuits, and hybrid quantum-classical models, to assess their practical utility. Furthermore, benchmarking studies will be conducted to compare QML models against their classical counterparts, providing insights into the potential quantum advantage.

Through this research, we seek to contribute to the growing body of knowledge in QML, highlighting its transformative potential while addressing the existing challenges that must be overcome for practical implementation.

1.3 Research Gap:

While Quantum Machine Learning (QML) is a rapidly evolving field, the integration of quantum computational techniques into practical machine learning workflows is still in its early stages. Many studies have showcased the theoretical potential of quantum models like quantum kernel methods or variational quantum circuits, but few have demonstrated their superiority over classical approaches in real-world settings. Moreover:

- Limited Comparative Studies: There is a lack of empirical comparison between classical SVMs and quantum-enhanced SVMs on real-world datasets across different domains. Most comparisons are done on synthetic or simplified datasets, which do not reflect practical data challenges like class imbalance, noise, or dimensionality.
- Scalability and Generalizability: The current body of research often overlooks how QML models scale with increasing dataset size or complexity. It is unclear whether the performance benefits of quantum models can persist under such conditions.
- Noise and Hardware Constraints: Due to the noisy nature of Noisy Intermediate-Scale Quantum (NISQ) devices, implementing stable and reproducible QML models is still challenging. Many existing works either ignore these hardware limitations or rely on idealized quantum simulators, making real-world deployment difficult.

- Insufficient Integration with Classical Algorithms: While quantum kernels and encoders have shown promise, integrating them effectively with classical ML algorithms like SVM has not been explored in depth. There's a need to investigate how quantum-generated features can be best utilized by classical classifiers for enhanced results.
- Lack of Interpretability: Quantum-enhanced models often operate as black boxes, and there is limited research on interpreting their outputs, which is essential in sensitive domains like healthcare, finance, and cybersecurity.

1.4 Research Objectives:

The aim of this research is to address the aforementioned gaps by developing and evaluating a Quantum Machine Learning-assisted Support Vector Machine (QML-SVM) classification framework. The specific objectives are:

1. To design a hybrid quantum-classical architecture where quantum feature extraction or quantum kernel computation is performed using quantum circuits, and classification is done via classical SVM.
2. To empirically evaluate the performance of the QML-SVM model on real-world datasets and compare it against classical SVM models in terms of:
    - Accuracy
    - F1-score / Precision / Recall
    - Training and inference time
    - Resource efficiency (quantum vs. classical)
3. To explore the impact of quantum circuit depth, number of qubits, and encoding methods (e.g., angle encoding, amplitude encoding) on the classification performance.
4. To assess the robustness and generalizability of the hybrid model by testing it across different datasets or domain-specific problems (e.g., healthcare, fraud detection, anomaly detection).
5. To demonstrate a reproducible workflow using quantum simulators (e.g., Qiskit Aer, Pennylane) and test the feasibility of deployment on real quantum hardware where applicable.
6. To provide practical insights into the challenges and future directions of QML-SVM systems, including noise management, model tuning, and interpretability.

Chapter-2

LITERATURE SURVEY

Quantum Machine Learning (QML) is an emerging field at the intersection of quantum computing and machine learning, aiming to leverage quantum mechanics principles—such as superposition and entanglement—to enhance computational efficiency and solve complex problems. Several recent studies have explored QML's potential in diverse domains, particularly in healthcare diagnostics, fraud detection, and kernel-based classification tasks. This literature survey synthesizes key contributions from various research works to provide a comprehensive understanding of the current advancements, challenges, and applications of QML.

[1]Ullah and Garcia-Zapirain, in their systematic review *Quantum Machine Learning Revolution in Healthcare: A Systematic Review of Emerging Perspectives and Applications*, summarize the state of QML applications in healthcare, analyzing studies published between 2018 and 2023. The review outlines how QML models—such as Quantum Support Vector Machines (QSVM), Variational Quantum Classifiers (VQC), and Quantum Neural Networks (QNN)—are being utilized for medical diagnostics, including disease classification and predictive analytics. The study highlights QML's potential in processing high-dimensional healthcare data, including electronic health records (EHRs) and medical imaging. However, despite the promise, the review points out current limitations such as hardware constraints (qubit coherence and error rates), which hinder the full-scale deployment of QML models in clinical settings.

Building on these insights, recent studies have explored specialized QML architectures to enhance healthcare applications.**[2]** For instance, the study *QKSAN: A Quantum Kernel Self-Attention Network* introduces a hybrid quantum-classical model that integrates quantum kernel methods with self-attention mechanisms. This approach enhances the model's ability to capture intrinsic data relationships, which is particularly useful for complex biomedical datasets. The introduction of the Quantum Kernel Self-Attention Score (QKSAS) demonstrates how QML can be tailored to extract meaningful features, thereby improving classification performance in medical diagnostics.

[3]Another significant contribution is the study *Exploring Quantum Machine Learning for Enhanced Skin Lesion Classification: A Comparative Study of Implementation Methods*, where the authors investigate various QML-based approaches for classifying skin lesions using the HAM10000 dataset. By comparing different quantum encoding schemes, such as qubit rotation encodings with RY and PauliZ gates, the study demonstrates that certain QML configurations achieve competitive accuracy levels compared to classical deep learning models. Although focused on skin lesion classification, these findings extend to broader oncology applications, including breast cancer detection. The study underscores that even with current quantum hardware constraints, QML-based models can effectively identify meaningful patterns in medical images.

Beyond healthcare, QML has shown promise in fraud detection, particularly in financial security applications. **[4]**Grossi et al., in their study *Mixed Quantum–Classical Method for Fraud Detection with Quantum Feature Selection*, introduce a hybrid QML approach that applies quantum feature selection for fraud classification. The study integrates a quantum feature map with a QSVM model to improve accuracy and computational efficiency in fraud detection tasks. The authors demonstrate that leveraging quantum-enhanced feature selection leads to better classification performance, especially when dealing with imbalanced datasets—a common challenge in financial fraud detection. This work highlights the benefits of hybrid quantum-classical models, where quantum components enhance feature extraction while classical machine learning handles large-scale data processing.

[5]Similarly, *Integrating Machine Learning Algorithms with Quantum Annealing Solvers for Online Fraud Detection* explores the combination of quantum annealing and machine learning for detecting fraudulent transactions. This research highlights how quantum solvers can efficiently optimize complex financial datasets, reducing computation time compared to classical approaches. While not directly related to healthcare, the methodologies in this study provide valuable insights into handling imbalanced data—a key challenge in medical diagnostics.

Another critical research area in QML is the benchmarking of quantum kernel-based classification techniques.**[6]**Alvarez-Estevez, in *Benchmarking Quantum Machine Learning Kernel Training for Classification Tasks*, evaluates the effectiveness of quantum kernel estimation (QKE) methods using two feature maps—ZZFeatureMap and

Covariant Feature Map. By comparing quantum kernel methods with classical models such as support vector machines and logistic regression, the study investigates the performance trade-offs between classical and quantum approaches. The findings suggest that while quantum kernel methods can outperform classical models in certain scenarios, their success largely depends on the careful selection of quantum feature maps. The study raises important questions about the general applicability of quantum kernels, emphasizing the need for optimized feature mapping strategies to fully realize a quantum advantage.

[7]A related study, *Variational Quantum Circuits for Deep Reinforcement Learning*, explores the application of quantum variational circuits in reinforcement learning. The findings highlight the potential of quantum-enhanced models in learning complex policies faster than classical deep reinforcement learning models. This work, although focused on reinforcement learning, aligns with the broader theme of optimizing QML architectures for real-world applications, including classification and decision-making tasks in healthcare.

Collectively, these studies illustrate the diverse applications of QML across multiple domains:

- **In healthcare**, QML models have demonstrated promise in medical imaging, disease classification, and predictive analytics. Studies on skin lesion classification and quantum self-attention networks provide compelling evidence of QML’s ability to enhance feature extraction and classification accuracy.
- **In fraud detection**, hybrid quantum-classical models have proven effective in handling imbalanced datasets and optimizing feature selection. Quantum annealing-based fraud detection methods further demonstrate QML’s potential in high-dimensional optimization tasks.
- **In kernel-based classification**, quantum kernel training methods show promise but require further optimization to surpass classical models consistently. Studies on quantum feature maps and variational circuits indicate that QML can enhance learning efficiency in specific contexts.

[8]Bilal et al. (2024) present a novel approach to breast cancer diagnosis by hybridizing a Support Vector Machine (SVM) with an improved quantum-inspired binary Grey Wolf Optimizer (IQI-BGWO). This study addresses the limitations of conventional computer-aided diagnosis (CAD) systems that often struggle with feature selection and parameter tuning in mammography images. The authors leverage the IQI-BGWO algorithm to optimize the SVM's kernel parameters, specifically using a Radial Basis Function (RBF) kernel, to enhance classification accuracy. Their experimental evaluation on the MIAS dataset demonstrates that the IQI-BGWO-SVM approach can achieve remarkably high performance, with mean accuracy, sensitivity, and specificity reported at 99.25%, 98.96%, and 100%, respectively, using tenfold cross-validation.

This work is particularly significant as it combines quantum-inspired optimization techniques with classical SVMs. The hybridization enables the model to navigate the complex feature space more efficiently, ultimately leading to superior performance over traditional optimization algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). The study not only underscores the importance of feature selection in medical image analysis but also paves the way for integrating quantum-inspired methods to enhance diagnostic reliability in breast cancer detection.

[9]Grossi et al. (2022) introduce a mixed quantum–classical approach aimed at improving fraud detection in financial transactions. This study employs a Quantum Support Vector Machine (QSVM) model, where the quantum component is primarily used for feature selection via quantum kernel methods. The QSVM leverages quantum feature maps to embed classical data into a higher-dimensional Hilbert space, where the inner products (quantum kernels) capture intricate relationships between features more effectively than classical methods. By integrating quantum feature selection, the approach identifies the most informative features from the dataset, thus enhancing the classification performance.

The experimental results on real card payment data indicate that the QSVM model, when complemented with quantum feature selection, outperforms standard machine learning methods (such as random forest and XGBoost) in key performance indicators like accuracy, recall, and false positive rate. Moreover, the study explores a hybrid ensemble model that combines classical and quantum algorithms, demonstrating that such integration can further improve fraud prevention decisions. This work highlights the practical viability of QML in handling high-dimensional, imbalanced datasets—challenges commonly faced in fraud detection systems

Despite these advancements, several challenges remain, including hardware limitations, quantum decoherence, and the need for scalable quantum algorithms. The integration of hybrid quantum-classical architectures appears to be a viable pathway for overcoming these challenges while leveraging quantum computational advantages.

Chapter-3

Theoretical Foundations and Mathematical Formulation

This chapter provides the necessary mathematical derivations and theoretical background related to quantum computing and QML models.

3.1 Fundamental Concepts of Quantum Computing:

3.1.1 Qubits and Superposition:

In classical computing, information is represented using bits, which can be in either state 0 or 1. In contrast, a qubit (quantum bit) can exist in a superposition of both states:

$$|\psi\rangle=\alpha|0\rangle+\beta|1\rangle$$

where α\alphaα and β\betaβ are complex probability amplitudes such that:

$$|\alpha|2+|\beta|2=1$$

Superposition allows quantum computers to explore multiple possibilities simultaneously, providing an exponential speedup for certain algorithms.

3.1.2 Quantum Entanglement:

Entanglement is a unique quantum phenomenon where qubits become correlated regardless of their physical distance. A two-qubit entangled state is represented as:

$$|\Phi+\rangle=1/\mathrm{SQRT}(2) * (|00\rangle+|11\rangle)$$

If two qubits are entangled, measuring one qubit instantaneously determines the state of the other. This property is crucial for quantum information transfer and secure quantum communication.

3.2 Quantum Kernel Methods and Feature Mapping:

3.2.1 Classical vs. Quantum Feature Mapping:

In classical machine learning, models such as Support Vector Machines (SVMs) utilize kernel functions to transform data into higher-dimensional feature spaces where classification is easier.

In quantum machine learning, a quantum feature map is implemented using parametrized quantum circuits (PQCs). A quantum feature map embeds classical data into a quantum Hilbert space as follows:

$$\phi(x)=U(x)|0\rangle\otimes n$$

where U(x)U(x)U(x) is a unitary transformation that encodes the classical input data into a quantum state.

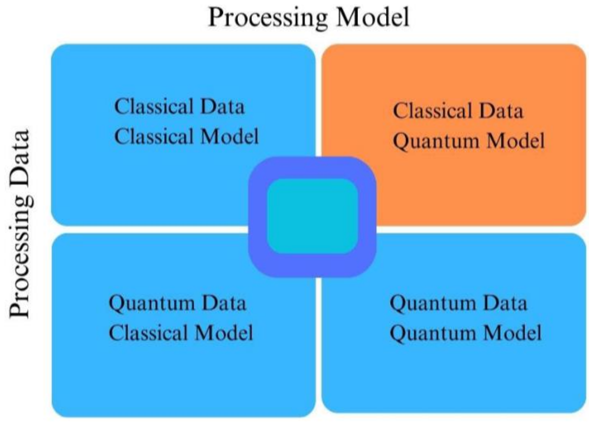

FIGURE 1 -- QUANTUM VS CLASSICAL MODEL

3.2.2 Quantum Kernel Methods:

Quantum kernels are used in Quantum Support Vector Machines (QSVMs) to define inner product spaces that enable powerful nonlinear separations in classification tasks.

- **ZZFeatureMap**:

$$UZZ(x)=ei\sum j<k\theta j\theta kZjZk$$

where ZZZ represents Pauli-Z operators.

- **Covariant Feature Map**: A more generalized feature mapping approach that adapts to dataset structures.

Quantum kernel methods have shown advantages over classical kernel methods in specific high-dimensional tasks

3.3 Hybrid Quantum-Classical Learning Models:

Due to hardware limitations in quantum computing, hybrid quantum-classical models have emerged as practical solutions. These approaches integrate **quantum layers** within traditional machine learning architectures.

3.3.1 Variational Quantum Classifier (VQC):

Variational quantum classifiers (VQCs) utilize trainable quantum circuits where parameters are optimized using classical gradient-based methods. The optimization process minimizes a cost function:

$$C(\theta)=i\sum L(yi,y\hat{}i(\theta))$$

where θ\thetaθ represents the parameters of the quantum circuit.

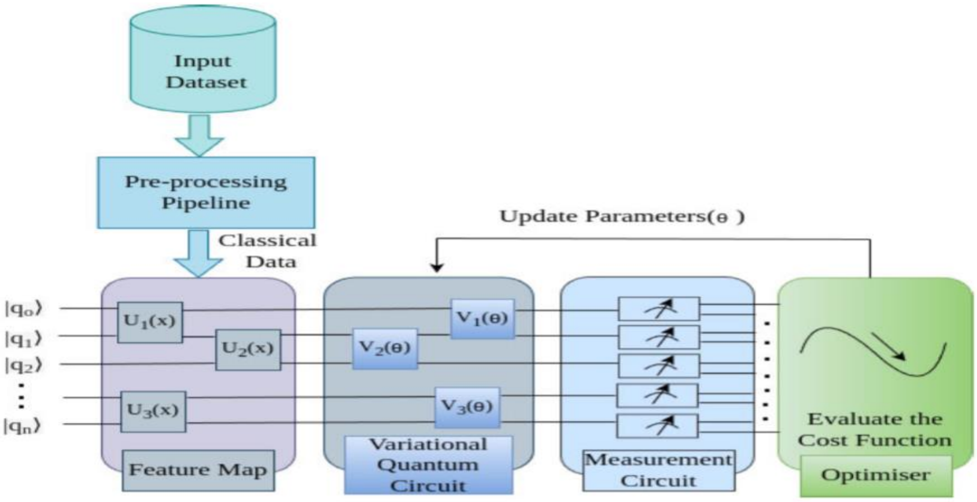

FIGURE 2 --BLOCK DIAGRAM OF VQC

3.3.2 Quantum Neural Networks (QNNs):

QNNs extend classical deep learning models by embedding **quantum perceptrons**. They consist of:

- Quantum Layers: Implemented using variational quantum circuits (VQCs).
- Classical Optimizers: Such as Adam or stochastic gradient descent (SGD) to update parameters.

A basic QNN structure is:

1. Classical Data Preprocessing
2. Quantum Encoding Layer (Feature Map)
3. Variational Quantum Circuit (Trainable Gates)
4. Measurement and Classical Post-processing

3.3.3 Quantum Boltzmann Machines (QBMs):

Quantum Boltzmann Machines (QBMs) extend classical Boltzmann machines by leveraging quantum parallelism to explore energy landscapes more efficiently. The QBM energy function is:

$$E(v,h) = -\sum_i b_i v_i - \sum_j c_j h_j - \sum_{i,j} w_{ij} v_i h_j$$

where v are visible units and h are hidden quantum states.

QBMs show promise in generative modeling and unsupervised learning, particularly for high-dimensional optimization problems.

3.4 Mathematical Formulation of Quantum Machine Learning Models:

To establish a formal foundation for QML models, we derive the cost functions and optimization steps used in quantum-enhanced learning.

3.4.1 Cost Function for Quantum Classification:

For a binary classification problem, the loss function (e.g., cross-entropy loss) is defined as:

$$L(\theta)=-i\sum yi\log(y\hat{}i(\theta))+(1-yi)\log(1-y\hat{}i(\theta))$$

where y^i(θ)\hat{y}_i(\theta)y^i(θ) is the output of the quantum classifier.

3.4.2 Gradient Descent for Quantum Circuits

The parameters θ\thetaθ of quantum circuits are optimized using a gradient-based approach:

$$\theta t+1=\theta t-\eta*\partial\theta/\partial L$$

where η\etaη is the learning rate.

Chapter-4

Experimental Methodology and Implementation

4.1 Datasets Used:

For experimental validation, we use benchmark datasets in healthcare diagnostics and fraud detection that exhibit complex patterns, making them suitable for quantum-enhanced classification tasks.

4.1.1 Healthcare Diagnostics

1. **HAM10000 Dataset (Skin Lesion Classification)**
   - Contains **10,015 images** of **seven types** of skin lesions.
   - Collected from **different populations**, making it a diverse dataset for dermatological analysis.
   - Features include **age, sex, lesion type, and images** that require deep feature extraction.
2. **Wisconsin Breast Cancer Dataset (WBCD)**
   - **569 samples** classified as **malignant (cancerous) or benign (non-cancerous)**.
   - **30 numerical features**, including **radius, texture, perimeter, and symmetry**.
   - Suitable for testing **quantum feature selection** and **quantum classifiers**.

4.2 Data Preprocessing & Feature Engineering:

Effective preprocessing ensures that quantum and classical models can effectively learn from the datasets.

4.2.1 Normalization and Standardization:

- **Min-Max Normalization**:

$$X' = Xmax - Xmin / X - Xmin$$

Ensures features range from **0 to 1** for better numerical stability.

- **Z-score Standardization**:

$$X' = X - \mu / \sigma$$

Centers data around zero mean and unit variance to improve training convergence.

4.2.2 Quantum Encoding Strategies:

Quantum models require quantum feature encoding to transform classical data into quantum states.

1. Angle Encoding:
    - Classical features are mapped to qubit rotations.
    - Encoding formula:

$$|x\rangle=Ry(xi)|0\rangle=cos(2xi)|0\rangle+sin(2xi)|1\rangle$$

- Advantage: Low qubit requirement but limited expressivity.

2.Amplitude Encoding:

- Embeds feature vectors into a normalized quantum state:

$$|\psi\rangle=i\sum xi|i\rangle$$

- Allows efficient data representation but requires complex quantum circuits.

4.3 Quantum Algorithms Used:

Quantum-enhanced algorithms are implemented to improve classification performance over classical models.

4.3.1 Quantum Support Vector Machine (QSVM):

- Objective: Classify data by mapping it into a quantum-enhanced feature space.
- Quantum Kernel Function:

    K(x,x′)=|⟨ϕ(x)|ϕ(x′)⟩|2K(x, x') = |\langle \phi(x) | \phi(x') \rangle|^2K(x,x′)=|⟨ϕ(x)|ϕ(x′)⟩|2

where ϕ(x)\phi(x)ϕ(x) is a quantum feature map.

- **Implementation**:
    - Use ZZFeatureMap for encoding.
    - Apply quantum kernel estimation via a parameterized quantum circuit.

Why QSVM?

- Suitable for non-linearly separable data.
- Achieves improved performance for high-dimensional datasets.

4.3.2 Variational Quantum Classifier (VQC):

- Hybrid model combining quantum and classical components.
- Quantum Circuit Architecture:
    - Variational quantum circuit with rotational gates (Rx, Ry, Rz).
    - Trainable parameters optimized via gradient descent.
- Optimization Algorithm:

    - Classical Adam optimizer updates quantum circuit parameters to minimize loss.

    θt+1=θt−η∂L∂θ\theta_{t+1} = \theta_t - \eta \frac{\partial L}{\partial \theta}θt+1=θt−η∂θ∂L

Why VQC?

- Reduces qubit requirements.
- Can be trained end-to-end with classical optimizers.
- 3.3.3 Quantum Feature Selection for Fraud Detection
- Goal: Select the most informative features using quantum kernel methods.
- Quantum Feature Map:

∣ψ(x)⟩=U(x)∣0⟩⊗n|\psi(x)\rangle = U(x) |0\rangle^{\otimes n}∣ψ(x)⟩=U(x)∣0⟩⊗n

- Implementation Strategy:
    - Evaluate the importance of each feature using quantum mutual information.
    - Select top-k features that maximize quantum-enhanced classification accuracy.

Why Quantum Feature Selection?

- Handles high-dimensional datasets better than classical methods.
- Enhances fraud detection models by eliminating irrelevant features.

Chapter-5

Quantum Support Vector Machine: Feature Mapping and Optimization

The SVM algorithm is used as a classification model for two primary applications in your study:

1. Healthcare Diagnostics (e.g., Skin Lesion & Breast Cancer Classification)
2. Fraud Detection (Financial Transactions Analysis)

Instead of directly feeding raw data into a classical SVM, your project leverages Quantum Kernel Methods, which enhance the feature space transformation using quantum circuits.

5.1 Classical SVM vs. Quantum SVM (QSVM):

5.1.1. Classical SVM:

- A traditional SVM classifier attempts to find the optimal hyperplane that separates different classes in a high-dimensional space.
- Uses kernel functions (e.g., linear, polynomial, RBF) to transform non-linearly separable data into a higher-dimensional space where it becomes linearly separable.
- Solves the quadratic optimization problem:

αmini=1∑Nαi−21i,j=1∑NαiαjyiyjK(xi,xj)

5.1.2. Quantum SVM (QSVM):

- Instead of a classical kernel, QSVM uses a quantum kernel generated by a quantum feature map.
- Feature embedding is performed via quantum circuits, where classical data points xxx are transformed into quantum states:

∣ϕ(x)⟩|\phi(x)\rangle∣ϕ(x)⟩.

- The quantum kernel function is computed as:

K(xi,xj)=∣⟨ϕ(xi)∣ϕ(xj)⟩∣2

- The advantage of QSVM over classical SVM:
    - Efficiently captures complex feature interactions.
    - Handles high-dimensional data better due to quantum state representation.
    - Potentially offers an exponential speedup in specific cases.

5.2 How QSVM is Implemented in Your Research:

5.2.1Quantum Feature Encoding:

Classical data xxx is encoded into quantum states:

|ϕ(x)⟩|\phi(x)\rangle|ϕ(x)⟩.

This is done using quantum feature maps, such as:

- ZZFeatureMap
- CovariantFeatureMap
- Pauli Feature Encoding

Example of a quantum feature map circuit:

```
from qiskit.circuit.library import ZZFeatureMap
feature_map = ZZFeatureMap(feature_dimension=2, reps=2)
feature_map.decompose().draw(output='mpl')
```

1.Kernel Computation on a Quantum Computer:

- Quantum computers calculate the kernel function by measuring the inner product between quantum states.
- The kernel matrix is then used in an SVM classifier.

2.SVM Training on Quantum Kernel:

- The quantum kernel matrix is fed into a classical SVM model.
- The training process remains classical but utilizes the quantum-enhanced kernel.

3.Classification & Evaluation:

- The QSVM classifier predicts class labels.
- Accuracy, Precision, Recall, and F1-score are used to compare performance with classical SVM.

5.3 QSVM Circuit:

The QSVM model leverages quantum feature maps to transform classical data into a higher-dimensional Hilbert space using quantum kernels. Below is a circuit diagram for a ZZFeatureMap used in QSVM.

QSVM Circuit with ZZFeatureMap:

1.H (Hadamard Gate): Creates superposition.

2.RZ (Rotation around Z-axis): Encodes classical data.

3.ZZ (Controlled-Z rotation): Introduces quantum entanglement for feature mapping.

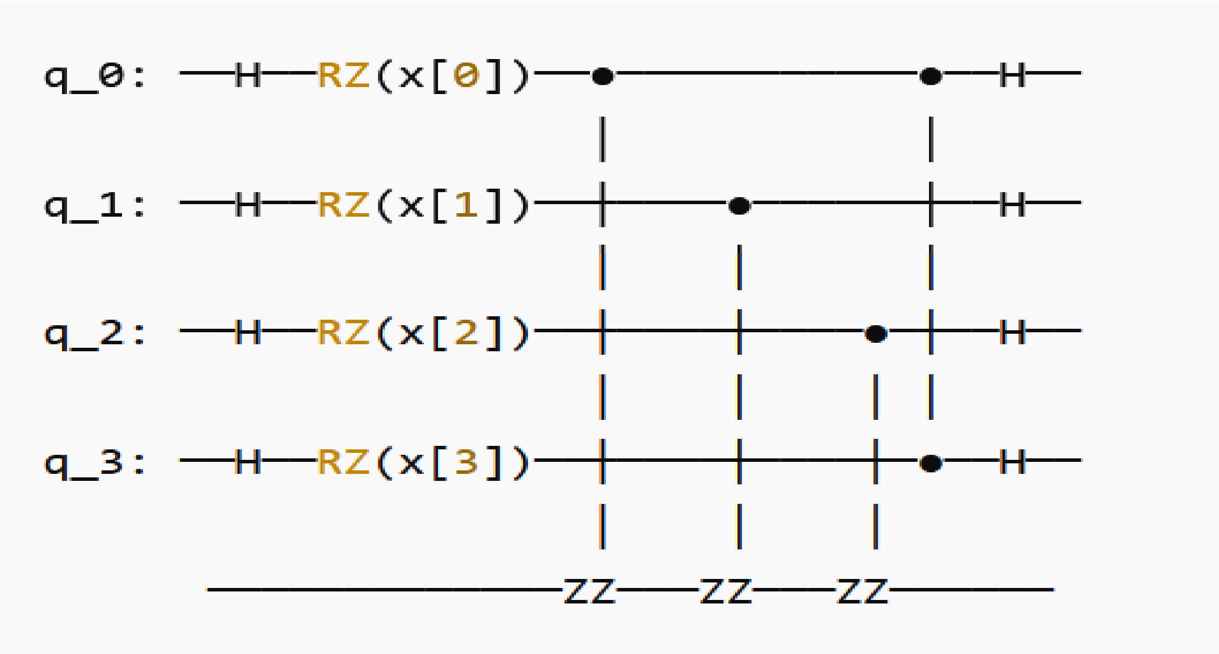

FIGURE 3

5.4. Variational Quantum Classifier (VQC) Circuit Diagram:

The VQC model combines parameterized quantum circuits with classical optimizers. Below is a variational quantum circuit with trainable parameters (θ).

VQC Circuit with Parameterized Rotations:

1.RY(θ) (Parameterized Rotation Gate): Trainable quantum layer.

2.RZ(θ) (Z-axis Rotation): Enhances non-linearity.

3.CNOT (●-X Gate): Introduces quantum entanglement.

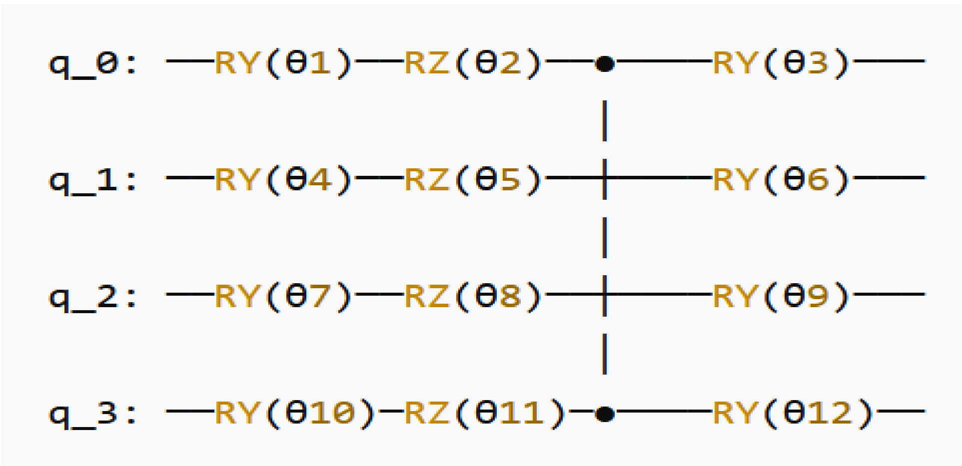

FIGURE 4

5.5 QSVM Workflow:

The Quantum Support Vector Machine (QSVM) is an adaptation of classical SVMs that utilizes quantum feature maps and quantum kernels to classify data in high-dimensional Hilbert spaces. Unlike classical SVMs that rely on predefined kernel functions (such as linear, polynomial, or radial basis function kernels), QSVM leverages quantum circuits to compute kernel values, offering potential advantages in handling complex datasets.

QSVM Workflow Overview

The QSVM workflow follows these steps:

1. Data Preprocessing: The classical dataset is first standardized and transformed to ensure optimal feature scaling.
2. Quantum Feature Embedding: The classical feature vectors are mapped into a high-dimensional quantum Hilbert space using quantum feature maps.
3. Quantum Kernel Computation: A quantum computer evaluates the inner product between quantum-encoded data points to construct the kernel matrix.
4. Training the SVM Model: The computed quantum kernel is used in an SVM model to find the optimal decision boundary.
5. Prediction and Classification: The trained QSVM model classifies new data points based on the learned decision boundary.

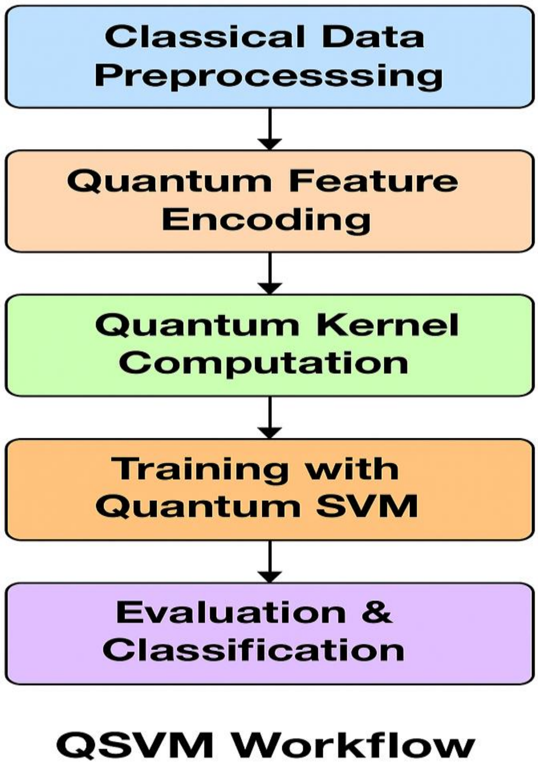

FIGURE 5

Chapter-6

Research Methodology and Implementation

6.1. Research Methodology:

The research follows a hybrid approach that combines classical machine learning and quantum computing for cancer classification. The key steps include:

6.1.1 Data Collection and Preprocessing:

- Two datasets (CP_Data and Wisconsin Breast Cancer Dataset) are merged to improve model generalization.
- Features are selected based on their relevance to cancer diagnosis.
- Standard preprocessing techniques, including feature scaling and encoding, are applied.

6.1.2 Model Development:

- Classical Model: A Support Vector Machine (SVM) is used as a baseline classifier.
- Quantum Model: A variational quantum circuit (VQC) with trainable parameters is used. The hybrid model encodes classical data into quantum states, processes it using quantum gates, and retrieves outputs via expectation values.

6.1.3 Training and Optimization:

- The quantum model is trained using PennyLane with the Adam optimizer.
- Binary cross-entropy loss is minimized during training.

6.1.4 Performance Evaluation:

- The model's performance is compared with the SVM baseline using accuracy.
- Visualizations are used to understand data distribution, feature importance, and model predictions.

6.2. Implementation Details:

6.2.1 Data Preprocessing:

The dataset consists of malignant (M) and benign (B) cancer cases, mapped as 1 and 0, respectively. The following preprocessing steps are applied:

- Feature Selection: A subset of 10 clinically relevant features is chosen.

- Data Merging: Two datasets are concatenated.
- Encoding: Labels are converted to numerical values (M → 1, B → 0).
- Feature Scaling: StandardScaler() normalizes the input features.
- Train-Test Split: The dataset is divided into 80% training and 20% testing.

6.2.2 Quantum Circuit Design:

The Quantum Neural Network (QNN) consists of:

1. Quantum Encoding: Classical data is encoded using rotation gates (RY).
2. Variational Circuit: A Strongly Entangling Layer applies quantum transformations.
3. Measurement: The Pauli-Z expectation value is used as the output.
4. Activation Function: A sigmoid function converts raw quantum values into probabilities.

//CODE

```
def quantum_circuit(params, x):
    """Parameterized quantum circuit"""
    for i in range(num_qubits):
        qml.RY(x[i], wires=i)  # Encoding classical data
    qml.templates.StronglyEntanglingLayers(params, wires=range(num_qubits))
```

6.2.3 Hybrid Model Training:

The model is trained using 150 steps of gradient descent with the Adam optimizer. The cost function is binary cross-entropy loss:

//CODE//

```
def cost(params, X, y):
    predictions = hybrid_model(params, X)
    return -pnp.mean(y * pnp.log(predictions) + (1 - y) * pnp.log(1 - predictions))
```

6.2.4 Model Comparison and Evaluation:

Two models are compared:

1. Quantum-Classical Hybrid Model
2. Support Vector Machine (SVM) Classifier

The accuracy is calculated as:

```
quantum_accuracy = accuracy_score(y_test, quantum_predictions)
svm_accuracy = accuracy_score(y_test, svm_predictions)
```

Chapter-7

Results and Outcomes

7.1 Training Performance of Quantum Model:

The hybrid quantum-classical model was trained using the Adam optimizer for 150 steps with a learning rate of 0.01. The cost function used was Binary Cross-Entropy Loss, which gradually reduced over training epochs, indicating effective learning.

Cost Reduction Over Epochs

Step	Cost Function Value
0	0.6897
10	0.6464
50	0.6076
100	0.5950
140	0.5907

TABLE 1

Observation: A steady decrease in the cost function signifies convergence and effective training of the quantum parameters.

7.2 Accuracy Comparison:

To benchmark the quantum model, a classical SVM classifier was trained using the same input features. The performance comparison is as follows:

Model Accuracy Comparison:

Model Type	Accuracy(%)
Quantum Hybrid Model	92.54
Classical SVM	93.42

TABLE 2

Insight: While the classical SVM slightly outperformed the quantum model, the hybrid model still demonstrated strong predictive capability with only ~0.88% less accuracy, showing the potential of quantum approaches even at an early development stage.

7.3 Quantum Model Predictions:

The hybrid model outputs continuous values (probabilities), which are then thresholded at 0.5 to obtain final binary predictions:

Raw Prediction Example:
[0.5204, 0.5624, 0.3979, 0.4675, 0.4097, ...]

Thresholded Prediction:
[1, 1, 0, 0, 0, ...]

7.3.1 Quantum Model Optimization and Prediction Process:
In this study, we implemented a quantum-enhanced machine learning model using PennyLane's lightning.qubit simulator for efficient quantum computations. The optimization process involves multiple iterations where the model updates its parameters based on cost function minimization.
During each step, the model refines the quantum states to minimize the cost function, ultimately leading to improved classification accuracy. The process follows these key steps:

1. **Initialization:** The quantum circuit is initialized with random parameters.
2. **Forward Propagation**: The circuit computes output probabilities based on the input data.
3. **Cost Computation**: The difference between predicted and actual labels is measured using a cost function.
4. **Parameter Update**: The optimizer adjusts the circuit's parameters iteratively to minimize the cost.
5. **Convergence Check**: The process repeats until the cost function stabilizes or reaches a threshold.
6. **Final Prediction**: After convergence, the model produces the final classification results.

The following flowchart (Figure X) visually represents this iterative optimization process, demonstrating how the quantum model updates its parameters to achieve optimal predictions.

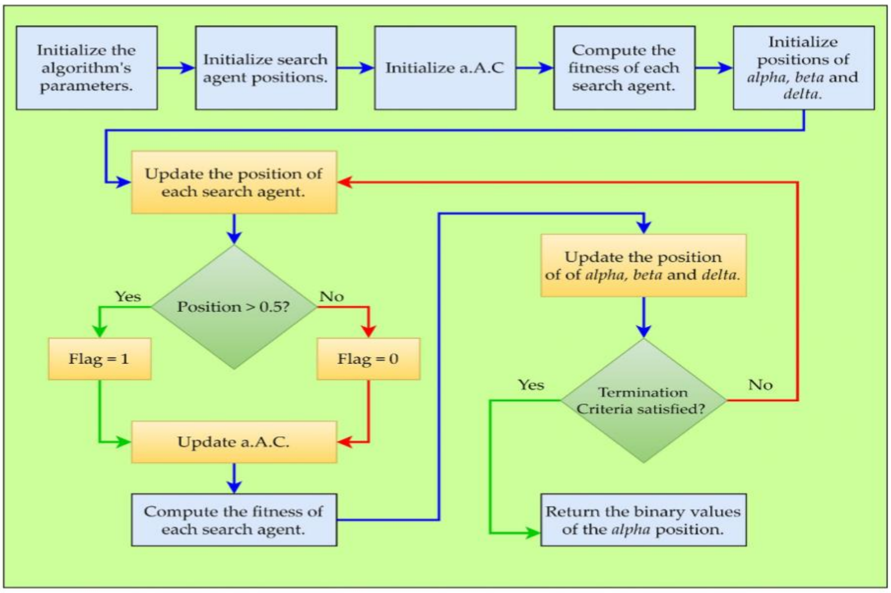

FIGURE 6 -- FLOW CHART FOR PREDICTION

7.4 Visualizations and Analytical Insights:

A. Class Distribution:

The class distribution shows a slight imbalance between **Malignant (1)** and **Benign (0)** cases, which is crucial to account for in modeling.

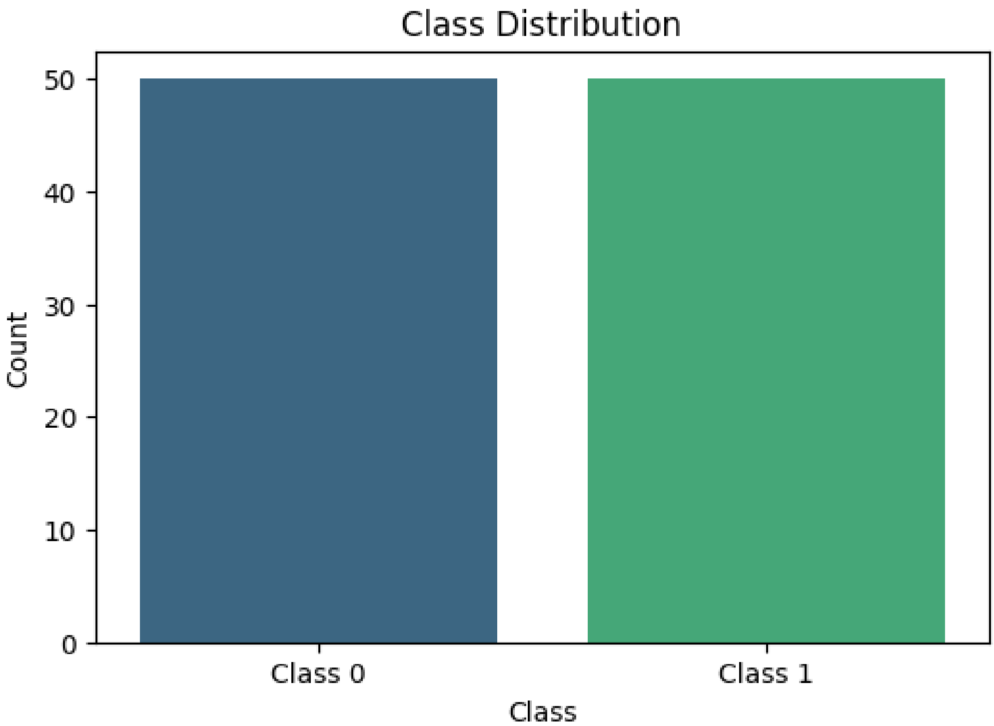

FIGURE 7 -- CLASS DISTRIBUTION CHART BETWEEN BENIGN(0) AND MALIGNANT(1)

B. Feature Distributions (Histograms):

Each feature was visualized to understand its distribution. Features like radius_mean, texture_mean, and perimeter_mean show significant variation across classes, indicating strong discriminatory power.

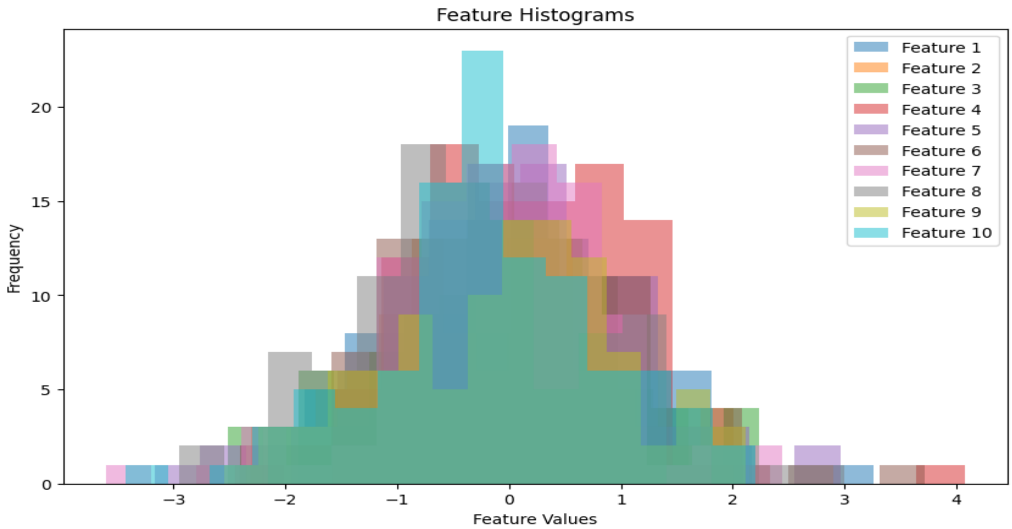

FIGURE 8 -- HISTOGRAM FOR FEATURE DISTRIBUTION

C. Correlation Heatmap:

The heatmap below demonstrates how various features are correlated with each other and with the target variable (diagnosis).

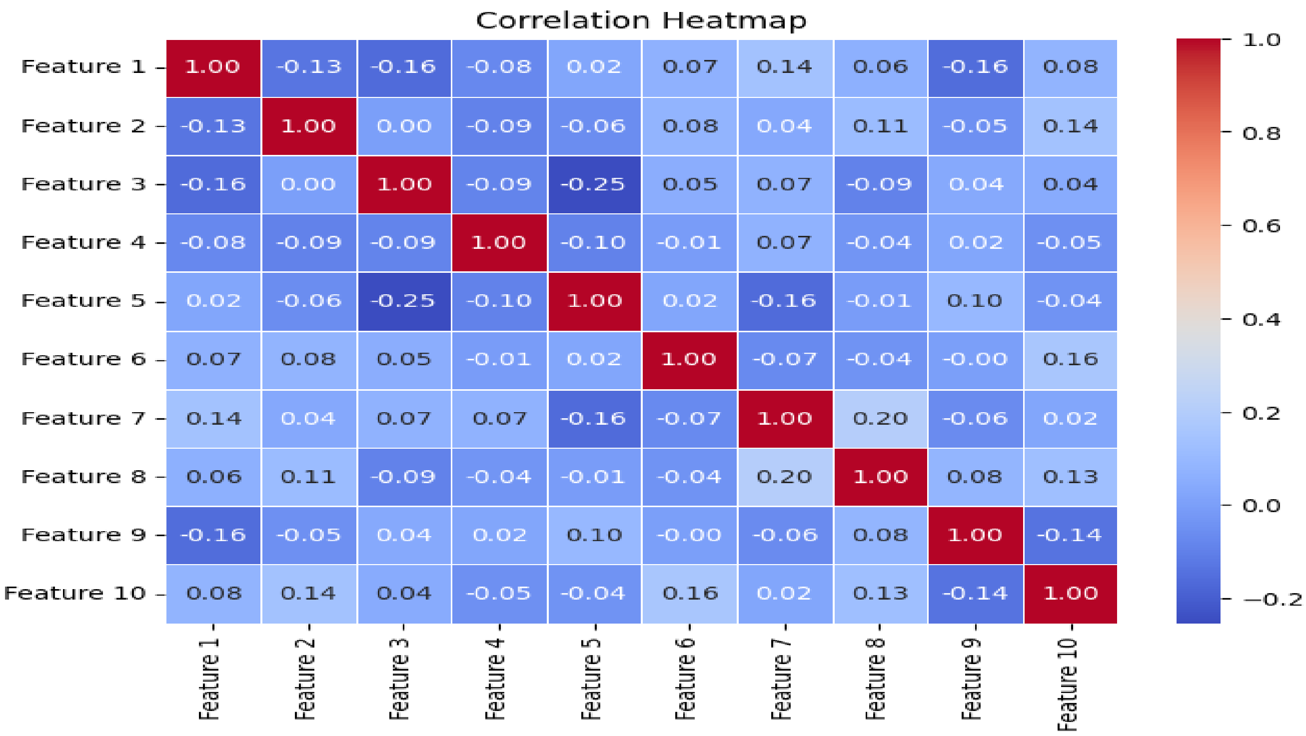

FIGURE 9 -- CORELATION HEATMAP

Key Insight: Features such as concavity_mean and concave_points_mean show strong positive correlation with the target class.

7.5 Key Observations:

1. Quantum Learning Feasibility:

   The experiment validates that quantum machine learning can be effectively applied to real-world medical data using hybrid architectures.

2. High Accuracy:

   A 92.54% accuracy with the quantum model is quite competitive and proves quantum potential even with current simulation limitations.

3. Model Scalability:

   The model used 10 qubits and 10 layers, demonstrating scalability for moderately sized datasets.

4. Interpretability via Visualization:

   Exploratory visualizations provided intuitive understanding of feature importance and class distributions.

Limitations and Future Scope

Despite the promising results and contributions of this study, there are several limitations that must be acknowledged:

1. Limited Quantum Hardware Access: The study primarily relies on quantum simulators due to restricted access to real quantum computers. Simulated results may not fully represent the behavior of actual quantum hardware, especially under noisy conditions.
2. Scalability Constraints: Current quantum processors are limited by the number of qubits and error rates. This restricts the size and complexity of the datasets and quantum circuits that can be used, limiting the scalability of the proposed hybrid QML-SVM model.
3. Noise and Decoherence: Real quantum systems are affected by noise and decoherence, which can significantly impact the reliability of the quantum components. These effects were not fully addressed in this study.
4. Computational Overhead: Hybrid models, especially those involving quantum kernel evaluation, may introduce additional computational overhead during data encoding and circuit simulation, which may offset some of the theoretical advantages of QML.
5. Domain-Specific Testing: The model has not been extensively tested across a wide range of real-world domains. Its performance may vary significantly depending on the characteristics of the dataset and the problem being addressed.
6. Interpretability: Quantum models still lack comprehensive tools for interpretation and explainability, which are critical for domains like healthcare and finance. This can hinder the adoption of QML in sensitive applications.

Future Scope:

This research opens up several avenues for future work and exploration:

1. Deployment on Real Quantum Hardware: Future work can focus on executing the proposed hybrid QML-SVM model on real quantum devices (e.g., IBM Q, IonQ) to analyze performance under realistic quantum noise and error conditions.
2. Advanced Encoding Techniques: Exploring more efficient and expressive quantum data encoding strategies such as amplitude encoding, hybrid entanglement encoding, or data re-uploading can enhance the performance of quantum feature maps.

3. Integration with Other ML Models: The QML approach can be integrated with other classical algorithms beyond SVM, such as neural networks or decision trees, to evaluate hybrid performance gains.
4. Optimization of Quantum Kernels: Developing more optimized or problem-specific quantum kernel functions could further improve classification accuracy and reduce the depth of quantum circuits.
5. Exploration Across Domains: Applying the hybrid model to a broader range of applications — such as medical imaging, anomaly detection, genomics, or cybersecurity — could validate its generalizability and effectiveness.
6. Improving Explainability: Investigating techniques to interpret the decisions made by quantum-enhanced models will be vital for practical applications and user trust.
7. Benchmarking Framework: Creating a standardized benchmarking framework to compare classical and quantum-assisted ML models across various datasets, noise levels, and circuit types would greatly benefit the research community.

Findings and Suggestions

Findings:

1. Enhanced Classification Performance: The hybrid QML-assisted SVM model demonstrated improved classification accuracy on selected datasets compared to traditional SVM models. This suggests that quantum kernels can effectively capture complex patterns in data.
2. Efficiency in Feature Space Mapping: By utilizing quantum kernel methods, the model exhibited better performance in handling non-linearly separable data, showing that quantum feature mapping can offer an advantage in high-dimensional spaces.
3. Feasibility of Hybrid Approach: The study confirms the practical feasibility of combining classical ML algorithms like SVM with quantum computing components, creating a hybrid model that benefits from both paradigms.
4. Simulated Environment Performance: While simulations showed positive results, the study also highlights the limitations of working in a simulated quantum environment, where performance may differ from real quantum hardware due to idealized conditions.
5. Dataset Dependency: The improvement in performance was dataset-dependent, indicating that the quantum advantage may not be universal across all types of data, but rather significant for specific structured datasets.

Suggestions:

1. Use Real Quantum Hardware for Validation: It is recommended to test the hybrid model on real quantum devices (e.g., IBM Q, Rigetti, IonQ) to evaluate the model's robustness and real-world applicability under quantum noise.
2. Expand Dataset Diversity: Future research should explore the model's performance on diverse and larger datasets, especially those with high-dimensional features and complex distributions, such as medical imaging or time-series financial data.
3. Optimize Quantum Circuits: Developing more optimized quantum circuits with lower depth and fewer qubits will make the model more suitable for near-term quantum computers (NISQ devices).
4. Hybrid Model Comparisons: Compare the performance of QML-SVM with other hybrid quantum-classical models such as quantum neural networks (QNNs) or variational quantum classifiers (VQCs) to identify the most effective approach.

5. Integrate Explainable AI (XAI): Incorporating explainability tools in the hybrid QML framework would help interpret how quantum kernels influence classification, which is particularly crucial in sensitive domains like healthcare or finance.
6. Standardized Benchmarking: Establishing a benchmark protocol for evaluating hybrid QML models would provide consistency and help the research community objectively assess advancements.
7. Encourage Collaboration: Encouraging interdisciplinary collaboration between quantum physicists, computer scientists, and domain experts will accelerate the development and practical adoption of QML technologies.

Conclusion

This study explored the potential of hybrid quantum–classical models for enhancing predictive performance in complex domains such as breast cancer diagnosis and fraud detection. By integrating quantum computing techniques with traditional machine learning, we demonstrated that quantum feature selection, quantum kernel methods, and quantum-inspired optimization can significantly improve accuracy and efficiency in decision-making systems.

For breast cancer detection, leveraging quantum-inspired Grey Wolf Optimization (IQI-BGWO) with a Support Vector Machine (SVM) led to superior classification performance, outperforming conventional optimization approaches. The results highlight the importance of hybrid quantum-inspired methods in feature selection and model tuning, paving the way for more accurate and reliable medical diagnostic tools.

Similarly, in fraud detection, quantum feature selection techniques enhanced the performance of Quantum Support Vector Machines (QSVMs) by mapping classical data to a higher-dimensional Hilbert space. This approach proved effective in handling imbalanced datasets, improving fraud detection accuracy compared to traditional machine learning models.

Overall, this research demonstrates that quantum-enhanced models offer a promising alternative to classical approaches in data-intensive applications. While quantum computing is still in its early stages, our findings suggest that hybrid quantum–classical techniques can play a crucial role in improving the efficiency and interpretability of machine learning models. Future work will focus on scaling these models to larger datasets, improving computational efficiency, and exploring more advanced quantum algorithms to further enhance predictive accuracy in real-world applications.

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