Comparative Analysis of Classical, Quantum, and Hybrid Machine Learning Models for Breast Cancer Classification

Submitted in partial fulfillment of the requirements for the degree of

Master of Science

In

Data Science

by

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<u>**DECLARATION**</u>

I hereby declare that the thesis entitled "**Comparative Analysis of Classical, Quantum, and Hybrid Machine Learning Models for Breast Cancer Classification** " submitted by me, for the award of the degree of *Master of Science in Data Science* to VIT is a record of bonafide work carried out by me under the supervision of **Dr. Raja Das.**

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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This is to certify that the thesis entitled "**Comparative Analysis of Classical, Quantum, and Hybrid Machine Learning Models for Breast Cancer Classification**" submitted by **Nishita Sunil Agrawal (Reg. No.: 24MDT0172)**, **School of Advanced Sciences**, VIT, for the award of the degree of *Master of Science in Data Science,* is a record of bonafide work carried out by him / her under my supervision during the period, **09.07.2025** to **14.11.2025**, as per the VIT code of academic and research ethics.

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Signature of the Student

ABSTRACT

Quantum computing represents an evolving realm of computational possibility. With quantum parallelism, superposition, and entanglement, it represents new avenues yet untapped for machine learning. At the same time, classical neural networks have been effective and computationally inexpensive for many applications in the real world where predictions are key. Thus, this thesis aims to analyze the performance of quantum, classical, and hybrid classifications of the same supervised learning problem relative to one another under the same exact parameters to better understand each independent approach in connection to the others.

Three models will be utilized: a classical Multilayer Perceptron (MLP), a fully quantum Variational Quantum Classifier (VQC) and a hybrid approach with a classical layer for dimension reduction and feature extraction as a pre-processing step before implementation of a parameterized quantum circuit. These models will be deployed on the Wisconsin Breast Cancer Diagnostic data set where no dimensionality reduction will be applied to ensure all 30 features exist prior to quantum treatment so as not to lose any information before potential processing.

The outcomes will be evaluated on training tendencies, general computational trends, parameter optimization, noise-resilience and ease of implementation on near-term quantum devices. Thus, rather than establishing one more effective than the other, a comparative analysis will be sought to understand the pros and cons of each with particular attention to how and why solutions in quantum or hybrid form can be more meaningful than justified current capabilities through classical means and what remains to be done to make such solutions reality on true quantum devices.

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List of Abbreviations

AI	Artificial Intelligence
AUC	Area Under the ROC Curve
CM	Confusion Matrix
FN	False Negative
FP	False Positive
HQC	Hybrid Quantum–Classical Model
LR	Learning Rate
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NN	Neural Network
NISQ	Noisy Intermediate-Scale Quantum
PQC	Parameterized Quantum Circuit
PR	Precision–Recall Curve
QC	Quantum Computing
QML	Quantum Machine Learning
QNN	Quantum Neural Network
QVC	Quantum Variational Circuit
VQC	Variational Quantum Classifier
ReLU	Rectified Linear Unit
ROC	Receiver Operating Characteristic
RMS	Root Mean Squared
TN	True Negative
TP	True Positive

1. INTRODUCTION

1.1. OBJECTIVE

The main goal of this work is to test how well three different models perform on the Breast Cancer dataset: standard neural networks (MLP), quantum-based classifiers (VQC), also hybrid setups combining both systems (HQC). Instead of assuming new methods are better, the analysis checks if quantum-assisted techniques actually improve results compared to classic ones - looking at precision, resource use, and speed.

1.2. MOTIVATION

The drive behind this work stems from my prior research titled "Preliminary Study of Quantum Neural Networks using NumPy," where I looked at elementary quantum-like networks through classical simulations. While doing so, I gained insight into core ideas - including qubit rotations, basic tunable circuits, and how quantum math functions behave computationally. Yet it became clear that pure theory can't fully reveal what Quantum Machine Learning might achieve. My past effort lacked actual variational setups, no support for physical devices was included, full-cycle training wasn't implemented either, nor any side-by-side tests against traditional deep learning methods. Because of these missing parts, I felt pushed toward exploring a deeper, hands-on approach.

Motivated by this gradual development, I chose to carry out a detailed, code-focused investigation - comparing Classical Neural Networks with Variational Quantum Classifiers (VQC) and Hybrid Quantum–Classical Models (HQC) using the Breast Cancer Diagnostic dataset, which is both authentic and delicate. Working independently, this task gives me the chance to explore how these methods vary in terms of learning patterns, ability to adapt to new data, resource demands, besides actual results. By doing so, I hope to see if quantum-based models provide tangible benefits today, or if combined frameworks might link classical speed with quantum flexibility instead. Moving from basic tests toward an in-depth comparison lies at the heart of why I'm pursuing this research.

1.3. BACKGROUND

Machine Learning (ML) is now widely practiced to support decisions based on data in areas like medicine, banking, online security, or science. Instead of relying solely on rules, systems can detect trends using examples. Neural networks - including types known as MLPs - perform well when handling organized numerical tables. Because they capture complex relationships, these methods often outperform simpler ones. Rather than just drawing straight lines, they model curves and interactions hidden in information. Thanks to years of testing and real-world use, traditional approaches are stable and fast. Training them has become easier due to techniques including backward error adjustment combined with update strategies like Adam or stochastic descent.

Alongside traditional machine learning's rise, a different kind of computing appeared - Quantum Computing (QC). Instead of using bits fixed as 0 or 1, these machines use quantum effects like superposition and entanglement. Thanks to such features, they handle intricate calculations and multidimensional operations beyond typical hardware limits. Because of this edge, scientists now test their potential in tasks involving optimization, searching, and identifying patterns. That effort gave birth to Quantum Machine Learning (QML), blending standard ML techniques with quantum-based processing.

In recent years, Variational Quantum Circuits (VQCs) emerged as a leading method in QML - especially suited for today's imperfect quantum hardware called NISQ devices. Instead of relying solely on quantum computation, these circuits transform classical data into quantum information via state encoding procedures. A sequence of adjustable quantum operations processes this encoded input; collectively, they’re referred to as a Parameterized Quantum Circuit (PQC). While the circuit manipulates quantum states, its performance depends heavily on tuning internal parameters - an optimization handled through conventional numerical techniques involving gradients computed classically. This mix creates what researchers call the Variational Quantum Algorithm (VQA), blending both computational paradigms seamlessly. Unlike traditional setups limited by architecture size, VQCs show potential due to their ability to model intricate patterns within data using relatively few qubits compared to equivalent neural networks.

Still, fully quantum approaches struggle with issues like noisy hardware, few available qubits, also problems such as barren plateaus that hinder learning progress. To tackle these hurdles, researchers suggest hybrid setups mixing quantum and classical components. These systems use quantum circuits for their strong representation ability, along with classical networks known for reliability and ease of scaling. Here, conventional layers handle early processing - like reducing data size - while quantum parts process condensed inputs. By combining both, the framework uses advantages from each side: traditional units deal well with big amounts of information, whereas quantum ones carry out operations potentially hard for standard methods.

The Breast Cancer Diagnostic data, applied in this work, serves as a common reference for categorization tasks. Featuring 30 numeric attributes taken from FNA scans of breast tissue anomalies, it offers consistent structure. Owing to moderate intricacy along with well-defined medical relevance, it works well for assessing algorithm performance. Because traditional machine learning frequently employs this collection, it becomes useful for examining feasibility of novel quantum approaches.

Previously, groundwork was laid via an earlier effort called “Preliminary Study of Quantum Neural Networks using NumPy,” which used standard software to mimic elementary quantum-like operations. Instead of theoretical ideas, focus shifted toward hands-on modeling - such as basic gate rotations, altering states, and hand-designed network layouts - to grasp how quantum setups process data. Yet, actual parametrized circuits weren't built back then; nor were learning behaviors tested or results stacked up against traditional networks. Building on those insights, this phase moves beyond imitation by applying authentic QML designs through tools like PennyLane and

PyTorch.

Because interest in quantum advantage is growing - yet proof that quantum machine learning beats classical techniques on small data remains weak - it’s key to test these methods through real experiments. This work helps clarify the situation by running classical, quantum, and combined models on one dataset, applying the same data preparation and testing rules across all. By looking closely at how each performs, how stable they are, their training patterns, and computing demands, we gain a clearer understanding of where QML stands today - and what part it might play in everyday ML tasks down the line.

2. PROJECT DESCRIPTION

This study examines three machine learning methods - Multilayer Perceptrons (MLP), Variational Quantum Classifiers (VQC), and Hybrid Quantum–Classical approaches (HQC) - applied to the Breast Cancer Diagnosis dataset; comparisons are made across multiple dimensions. Rather than simply measuring accuracy, it explores differences in training dynamics, feature representation strength, ability to adapt to new data, along with resource demands during execution. While MLP relies solely on classical computation, VQC uses parameterized quantum circuits within optimization loops, whereas HQC integrates both computing styles in layered structures. Because each method tackles the same two-class prediction problem, results allow insight into where quantum-based strategies may add value - or fail to outperform traditional tools - in real-world modeling scenarios.

The Classical setup works as a reference point; it uses a Multilayer Perceptron fed with all 30 features. This reflects how stable traditional deep learning methods can be. Instead of classical processing, the Quantum version applies a Variational Quantum Circuit - input data gets transformed into quantum states via rotational encoding, then processed through tunable quantum operations. While showing strong modeling power, this approach faces constraints from current quantum devices. Combining both worlds, the Hybrid method processes inputs classically at first, then passes them to a small quantum network. By doing so, it cuts down on needed qubits yet still tries to use quantum advantages, offering a balanced middle path.

The project covers full implementation of all three models - from preprocessing to visualization, including training and evaluation. Instead of just accuracy, measures like F1 Score, ROC–AUC, and Confusion Matrix are used to check how well classification works. To explore model behavior further, outputs include loss trends, probability spreads, calibration graphs, along with radar-based comparisons. For quantum parts, PennyLane is applied; meanwhile, standard tools like NumPy, PyTorch, and Scikit-Learn handle classical processing in Python.

This work compares methods systematically to explore what today's quantum machine learning can actually do. Because it expands on a prior test involving neural networks built with NumPy, the focus shifts toward working quantum setups combined with traditional models. As a result, we gain clearer understanding about how these approaches perform versus standard machine learning right now and where they might lead later.

PROJECT GOALS

i. To build a classical MLP model as a baseline for comparison.

ii. To implement a pure Variational Quantum Classifier (VQC).

iii. To design a Hybrid Quantum–Classical (HQC) model combining classical and quantum layers.

iv. To train all three models on the Breast Cancer Diagnostic dataset.

v. To evaluate models using Accuracy, F1 Score, ROC–AUC, and Confusion Matrices.

vi. To compare the training behavior and performance of classical vs quantum vs hybrid systems.

vii. To analyze whether quantum or hybrid models provide any practical advantage.

3. TECHNICAL SPECIFICATIONS

This project was developed using Python with essential ML and QML libraries including NumPy, Pandas, Scikit-Learn, PyTorch, Matplotlib, Seaborn, and PennyLane. All experiments were executed on a standard laptop with a multi-core CPU and 8–16 GB RAM. Quantum models were simulated using PennyLane's default.qubit backend, while classical and hybrid models were trained in Jupyter Notebook for easy visualization and reproducibility.

4. DESIGN APPROACH AND DETAILS

4.1 MATERIALS, APPROACH AND METHODS

Materials

In this project, Python serves as the main coding platform because it supports traditional and quantum machine learning well. As a result, these tools, libraries, and frameworks provide the foundation for building models

- **NumPy** handles numbers, works with tensors, and also manages model settings when preparing data and grouping it.
- **Pandas** Loads the Breast Cancer Diagnostic data, cleans it, then organizes it into DataFrames - also used for basic stats using tools like mean or count.
- **Scikit-Learn** (SKL) offers key machine learning tools; for instance, StandardScaler adjusts feature scales. Data splitting uses train_test7split to separate sets. Performance checks rely on metrics like accuracy or F1 score. ROC–AUC measures class separation quality. Confusion matrices show prediction breakdowns.
- **Matplotlib** together with **Seaborn** helps create graphs like loss trends, ROC lines, confusion tables, chance-based histograms, calibration visuals, also radar

diagrams showing how models differ.

- **PyTorch** handles the standard MLP setup along with traditional parts of the mixed model. For this, it delivers tools that compute gradients automatically instead of manual coding. Its design supports adaptable layers for networks rather than rigid templates. Performance during training benefits from fast error propagation methods built in.
- **PennyLane** serves as the main QML platform for designing and testing Variational Quantum Circuits (PQCs). Instead of relying on hardware, it uses its built-in default.qubit tool to process inputs through quantum logic. This simulator handles feature encoding while also managing gate operations. It computes expected outcomes from measurements. Moreover, it supports gradient calculations by tracking changes in circuit settings.
- **Jupyter Notebook** served as the workspace, enabling step-by-step processing; it supported visual displays while helping interpret findings through responsive interaction.

These tools combined create the basic computing and analysis setup needed to train, test, or contrast classical (MLP), quantum (VQC), and hybrid (HQC) models reliably and efficiently.

Approach

This study develops three distinct machine learning models, trains them using one shared dataset, while testing all under matching settings. It compares traditional computing with fully quantum approaches, along with mixed techniques, aiming to explore advantages, limitations, and real-world feasibility across different setups.

a. Dataset-Oriented Design

The Breast Cancer Diagnostic data includes 569 cases, each with 30 numeric attributes taken from scanned tumor pictures. Because of this, every model uses the same set for training, which helps maintain uniformity across results. This method leads to reliable comparisons between different techniques

- No dimensionality reduction - kept this way to ensure fair comparisons

- Identical train-test split
- Equal preprocessing techniques

b. Building a Strong Classical Baseline (MLP)

The traditional MLP aims initially at building a reliable reference point.

It:

- Uses all features
- Contains several densely linked layers
- Uses ReLU activation
- Is optimized with Adam

This shows what "good results" mean in classic machine learning.

c. Designing a Variational Quantum Classifier (VQC)

The VQC follows QML principles:

- A limited number of features - matching the qubit count - is selected for encoding; others are left out
- Features are mapped using RY rotations
- Trainable PQC layers include RX and RZ gates
- CNOT helps create entanglement between qubits by linking their states through conditional operations
- Circuit results show average outcomes
- Predictions come from setting a cutoff on these numbers

This method checks if quantum circuits are able to mimic decision borders.

d. Constructing a Hybrid Quantum–Classical Model (HQC)

The HQC brings together key aspects from each approach - using features from one alongside elements of the other - to form a unified framework

- Classic projection simplifies data by lowering dimensions
- Projected features enter a PQC
- Results from the quantum circuit go into a last classical stage

- The whole system can be trained from start to finish

This method checks if combined systems perform more effectively compared to strictly traditional ones.

e. Evaluation Strategy

All models undergo evaluation through:

- Accuracy
- F1 Score
- ROC–AUC
- Confusion Matrices
- Loss curves
- ROC curves
- Radar charts

The side-by-side analysis reveals:

- How quantum and hybrid models learn
- Do quantum circuits experience instability?
- Do traditional methods still outperform others when data is limited?

f. Building on My Previous Study

My earlier project, “Preliminary Study of QNN using NumPy,” provided experience with:

- Basic rotation gates
- Quantum-inspired operations
- Manual gradient exploration

This project elevates that foundation into:

- Full PQC pipelines
- Real QML frameworks
- Training plus testing from start to finish**.**

Methods

a. Data Preprocessing

Standardization

The dataset’s attributes vary in scale, therefore the script adjusts them by removing the average value while scaling via standard deviation. As a result, this improves performance

- stabilize training
- speed up convergence
- stop big elements from overshadowing little ones

Mathematical Representation

$$x' = (x - \mu)/\sigma$$

Train–Test Split

The dataset is divided into training (80%) and testing (20%) sets using *stratified sampling* so the class ratio is preserved.

Mathematical Representation

$$(X_{\{train\}}, y_{\{train\}}), (X_{\{test\}}, y_{\{test\}})$$

b. Classical Model

Forward Pass

The MLP receives an input vector with 30 dimensions.

Each layer performs:

- A linear change using matrix math along with an offset
- A ReLU activation keeps positives unchanged while turning negatives into zero

This enables the system to capture curved separation patterns**.**

Layer 1

$h_1 = ReLU(W_1x + b_1)$

Layer 2

$h_2 = ReLU(W_2h_1 + b_2)$

Output Layer

$z = W_3h_2 + b_3$

Softmax

The last layer outputs two raw scores. Softmax converts these scores into probabilities for the two classes.

Loss Function

The MLP uses Cross-Entropy Loss to compare predicted probabilities with true labels.

$\boldsymbol{L_{\{CE\}} = -\sum y_i(ln\widehat{y_i})}$

Backpropagation

The optimizer updates weights by computing gradients of the loss.

$\theta := \theta - \eta * \frac{\partial L}{\partial \theta}$

c. Variational Quantum Classifier

Feature Encoding

Each input feature is converted into a qubit rotation.

$|\psi(x)\rangle = \prod RY(x_i), |0\rangle$

RY rotation matrix:

$$\boldsymbol{RY(\theta)} = \begin{bmatrix} \left[\mathbf{cos}\left(\frac{\theta}{2}\right) & -\mathbf{sin}\left(\frac{\theta}{2}\right)\right] \\ \left[\mathbf{sin}\left(\frac{\theta}{2}\right) & \mathbf{cos}\left(\frac{\theta}{2}\right)\right] \end{bmatrix}$$

Variational Layer

The circuit applies trainable quantum rotations (RX and RZ) to each qubit**.**

$U(\theta) = \prod RX\left(\theta_{\{i1\}}\right)RZ\left(\theta_{\{i2\}}\right)$

Where:

$$\boldsymbol{RX(\alpha)} = \begin{bmatrix} \left[\mathbf{cos}\left(\frac{\alpha}{2}\right) & -\boldsymbol{i}\,\mathbf{sin}\left(\frac{\alpha}{2}\right)\right] \\ \left[-\boldsymbol{i}\mathbf{sin}\left(\frac{\alpha}{2}\right) & \mathbf{cos}\left(\frac{\alpha}{2}\right)\right] \end{bmatrix}$$

$$\boldsymbol{RZ}(\,\boldsymbol{\beta}\,) = \begin{bmatrix} [\,\boldsymbol{e^{-i\beta/2}} & \mathbf{0}] \\ [\,\mathbf{0} & \boldsymbol{e^{i\beta/2}}\,] \end{bmatrix}$$

Entanglement

Your circuit applies CNOT gates to entangle qubits.

$CNOT\left(q_i, q_{\{i+1\}}\right)$

Entanglement allows the circuit to learn more complex decision boundaries.

Measurement

The circuit returns the expectation value of the Pauli-Z operator on the first qubit.

$\hat{y} = \langle Z \rangle$

Where Z is the Pauli-Z observable:

$Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$

LossFunction

The VQC uses Mean Squared Error (MSE).

$L_{\{MSE\}} = \left(\frac{1}{N}\right) \sum (\hat{y}_i - y_i)^2$

Labels are remapped to -1and +1.

Quantum Gradient Computation

PennyLane uses the parameter-shift rule to compute quantum gradients.

$\frac{\partial f}{\partial \theta} = \frac{\left[f\left(\theta + \frac{\pi}{2}\right) - f\left(\theta - \frac{\pi}{2}\right)\right]}{2}$

d. Hybrid Quantum Classical Model

This part mixes classical and quantum layers.

Classical Dimensionality Reduction

It reduces 30 features → 4 features using a fully connected layer + tanh**.**

$h = tan(Wx + b)$

Quantum Processing

The compressed vector is encoded into a PQC using RY rotations → variational gates → CNOT entanglement.

$|\psi(h)\rangle = U(\theta) RY(h_i) |0\rangle$

Final Classical Layer

Quantum expectation values are stacked:

$q = [\langle Z_1 \rangle, \langle Z_2 \rangle, \dots]$

Quantum outputs are passed through a linear classifier to produce logits.

$\hat{y} = W_q q + b_q$

End-to-End Training

Both classical & quantum parameters are optimized:

$\theta_{\boldsymbol{classical}} \leftarrow \theta - \eta \nabla L$

$\theta_{\boldsymbol{quantum}} \leftarrow \theta - \eta \nabla L$

Because PennyLane connects quantum circuits with PyTorch **autograd.**

e. Performance Metrics

Code evaluates all three models using Scikit-Learn metrics

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

$$F1 = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

$$TPR = \frac{TP}{(TP + FN)}$$

$$FPR = \frac{FP}{(TP + FP)}$$

f. Visualization

The code produces:

- Loss curves
- ROC curves
- Confusion matrices
- Probability histograms
- Precision–Recall curves
- Radar chart comparing all models

4.2 CODES AND STANDARDS

a. Data Preprocessing:

```
import numpy as np
import pandas as pd
import random
import torch
import torch.nn as nn
from sklearn.datasets import load_breast_cancer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Reproducibility
seed = 42
np.random.seed(seed)
```

```
torch.manual_seed(seed)
random.seed(seed)

# Load dataset
data = load_breast_cancer()
X = data.data
y = data.target

# Standardization
scaler = StandardScaler()
X = scaler.fit_transform(X)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

# Convert to tensors for classical + hybrid models
X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
X_test_tensor  = torch.tensor(X_test, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train, dtype=torch.long)
y_test_tensor  = torch.tensor(y_test, dtype=torch.long)
```

b. Classical Model (MLP):

```
class ClassicalNN(nn.Module):
    def __init__(self, input_dim=30, n_classes=2):
        super().__init__()
        self.model = nn.Sequential(
            nn.Linear(input_dim, 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, n_classes)
        )

    def forward(self, x):
        return self.model(x)

model_classical = ClassicalNN()
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model_classical.parameters(), lr=0.001)

# Training loop
epochs = 50
for epoch in range(epochs):
    optimizer.zero_grad()
    outputs = model_classical(X_train_tensor)
    loss = criterion(outputs, y_train_tensor)
    loss.backward()
    optimizer.step()
```

```
# Evaluation
with torch.no_grad():
    test_logits = model_classical(X_test_tensor)
    preds = torch.argmax(test_logits, dim=1)

acc_classical = accuracy_score(y_test, preds)
f1_classical = f1_score(y_test, preds)
auc_classical = roc_auc_score(y_test, test_logits[:,1].numpy())
```

c. Variation Quantum Classifier:

```
import pennylane as qml
from pennylane import numpy as qnp

# Quantum settings
 n_qubits = 4
 dev = qml.device("default.qubit", wires=n_qubits)

 @qml.qnode(dev, interface="autograd")
 def vqc_circuit(x, weights):
        # Feature encoding using first n_qubits
         for i in range(n_qubits):
                  qml.RY(x[i], wires=i)

         # Variational block
        for i in range(n_qubits):
            qml.RX(weights[i,0], wires=i)
            qml.RZ(weights[i,1], wires=i)

        # Entanglement
        for i in range(n_qubits - 1):
            qml.CNOT(wires=[i, i+1])

        return qml.expval(qml.PauliZ(0))

# Prepare quantum labels
y_train_q = 2 * y_train - 1
y_test_q  = 2 * y_test  - 1

weights = qnp.random.randn(n_qubits, 2, requires_grad=True)
optimizer = qml.GradientDescentOptimizer(stepsize=0.1)

def vqc_predict(X, weights):
    return np.array([vqc_circuit(x[:n_qubits], weights) for x in X])

# Train VQC
epochs = 30
for epoch in range(epochs):
    def cost(weights):
        preds = vqc_predict(X_train, weights)
        return ((preds - y_train_q) ** 2).mean()
        weights = optimizer.step(cost, weights)
```

# Evaluate VQC

```
preds_vqc_cont = vqc_predict(X_test, weights)
preds_vqc = (preds_vqc_cont > 0).astype(int)
probs_vqc = (preds_vqc_cont + 1) / 2

acc_vqc = accuracy_score(y_test, preds_vqc)
f1_vqc = f1_score(y_test, preds_vqc)
auc_vqc = roc_auc_score(y_test, probs_vqc)
```

d. Hybrid Quantum- Classical Model:

# Hybrid QNode

```
@qml.qnode(dev, interface="torch")
def hybrid_qnode(x, weights):
    for i in range(n_qubits):
        qml.RY(x[i], wires=i)

    for i in range(n_qubits):
        qml.RX(weights[i,0], wires=i)
        qml.RZ(weights[i,1], wires=i)

    for i in range(n_qubits - 1):
        qml.CNOT(wires=[i, i+1])
    return [qml.expval(qml.PauliZ(j)) for j in range(n_qubits)]


class HybridModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(30, n_qubits)
        self.q_weights = nn.Parameter(torch.randn(n_qubits, 2))
        self.fc2 = nn.Linear(n_qubits, 2)


    def forward(self, x):
        x = torch.tanh(self.fc1(x))
        q_out = [hybrid_qnode(x[i], self.q_weights) for i in range(len(x))]
        q_out = torch.stack([torch.tensor(v) for v in q_out])
        return self.fc2(q_out)


model_hybrid = HybridModel()
optimizer = torch.optim.Adam(model_hybrid.parameters(), lr=0.01)


for epoch in range(years):
    optimizer.zero_grad()
    out = model_hybrid(X_train_tensor)
    loss = criterion(out, y_train_tensor)
    loss.backward()
    optimizer.step()
```

```
# Evaluation
with torch.no_grad():
    logits = model_hybrid(X_test_tensor)
    preds_hybrid = torch.argmax(logits, dim=1)

acc_hybrid = accuracy_score(y_test, preds_hybrid)
f1_hybrid = f1_score(y_test, preds_hybrid)
auc_hybrid = roc_auc_score(y_test, logits[:,1].numpy())
```

e. Model Evaluation Visualisation

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.metrics import (
    precision_recall_curve,
    roc_curve
)
from sklearn.calibration import calibration_curve

# Accuracy Curve
def plot_accuracy_curve(acc_list, title="Accuracy Curve", fname=None):
    plt.figure(figsize=(6,4))
    plt.plot(acc_list, marker='o')
    plt.title(title)
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.grid(True)
    if fname: plt.savefig(fname)
    plt.show()
```

# F1 Curve

```
def plot_f1_curve(f1_list, title="F1 Score Curve", fname=None):
    plt.figure(figsize=(6,4))
    plt.plot(f1_list, marker='o', color="green")
    plt.title(title)
    plt.xlabel("Epoch")
    plt.ylabel("F1 Score")
    plt.grid(True)
    if fname: plt.savefig(fname)
    plt.show()
```

# Precision Recall

```
def plot_precision_recall(y_true, y_prob, title="Precision-Recall Curve", fname=None):
    p, r, _ = precision_recall_curve(y_true, y_prob)
    plt.figure(figsize=(6,5))
    plt.plot(r, p)
    plt.title(title)
    plt.xlabel("Recall")
    plt.ylabel("Precision")
    plt.grid(True)
    if fname: plt.savefig(fname)
    plt.show()

# Probability Histogram
def plot_probability_hist(y_prob, title="Probability Distribution", fname=None):
    plt.figure(figsize=(6,4))
    sns.histplot(y_prob, bins=20, kde=True)
    plt.title(title)
    plt.xlabel("Predicted Probability")
    plt.ylabel("Count")
    if fname: plt.savefig(fname)
    plt.show()

# Calibration Curve
def plot_calibration_curve(y_true, y_prob, title="Calibration Curve", fname=None):
    prob_true, prob_pred = calibration_curve(y_true, y_prob, n_bins=10)
    plt.figure(figsize=(6,5))
    plt.plot(prob_pred, prob_true, marker='o')
    plt.plot([0,1],[0,1],'--')
    plt.title(title)
    plt.xlabel("Predicted Probability")
    plt.ylabel("True Probability")
plt.grid(True)

if fname: plt.savefig(fname)

plt.show()
```

5. SCHEDULE, TASKS AND MILESTONES

S.NO	**MONTH-WEEK**	**PLAN**
1.	JULY- WEEK 1	Identification of the problem.
2.	JULY- WEEK 2, 3	Literature review on the decided problem.
3.	JULY- WEEK 4	Discussion on the aims, objectives and outcomes of the problem.
4.	AUGUST-WEEK 1	Formation of abstract.
5.	AUGUST-WEEK 2,3,4	Collection of data.
6.	SEPTEMBER-WEEK 1,2,3,4	Methodology: Adaptation of the appropriate methods for the gathered data.
7.	OCTOBER- WEEK 1,2	Appropriate analysis, relevant discussion and valid conclusions.
8.	OCTOBER- WEEK 3	Feedback from guide.
9.	OCTOBER- WEEK 4	Final documentation and report writing.

10.	NOVEMBER - WEEK 1,2	Report review
11.	NOVEMBER – WEEK 3	Final review

Table 1

6. PROJECT OUTPUTS

- **Classical Neural Network**

Model Architecture Diagram

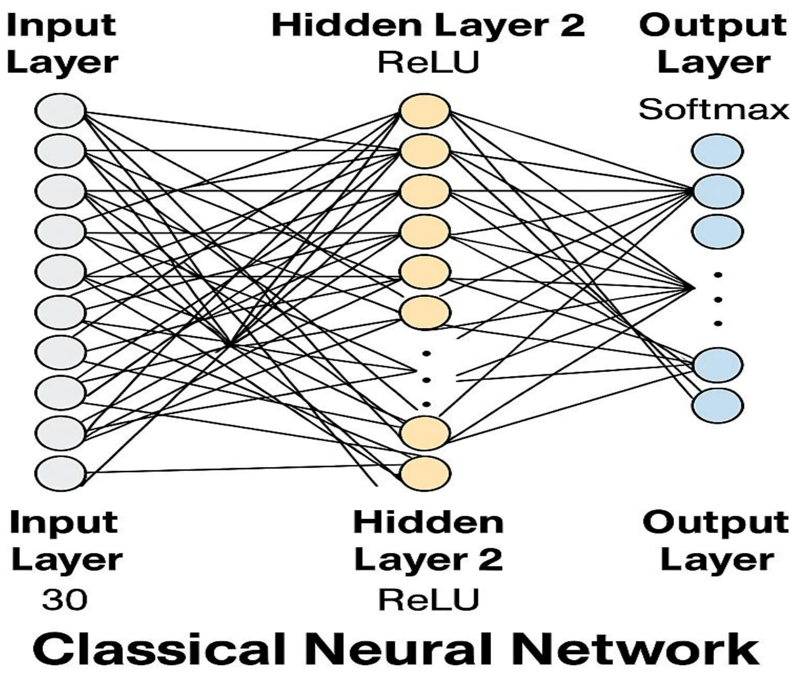

Figure 1

Loss Curve

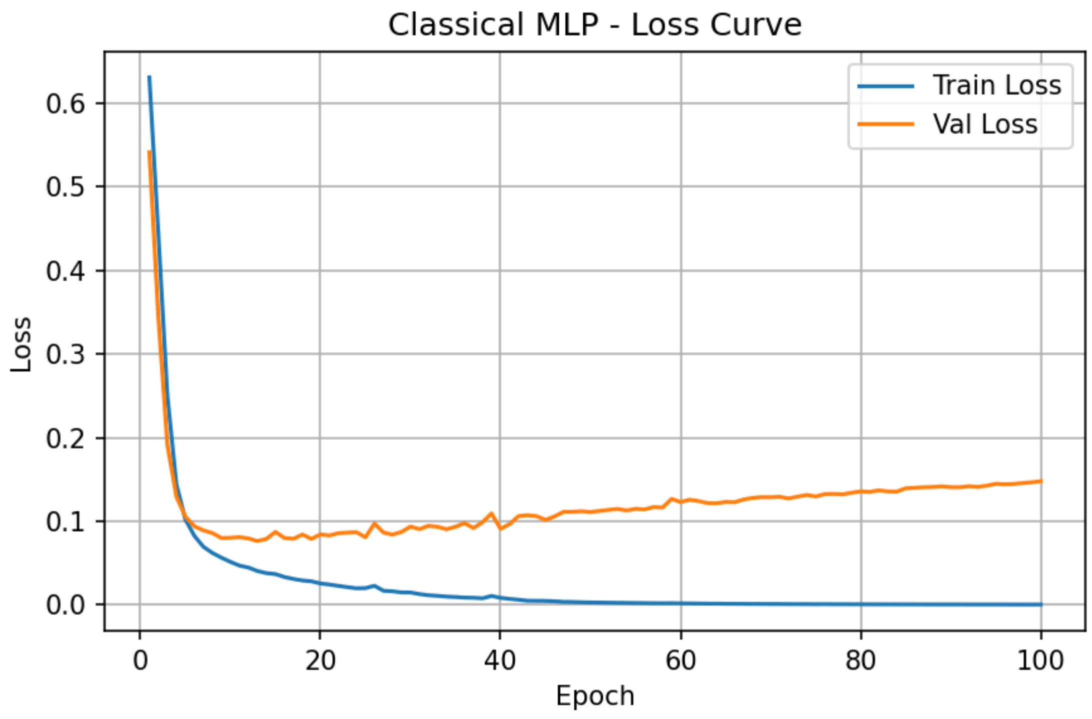

Figure 2

Validation Accuracy

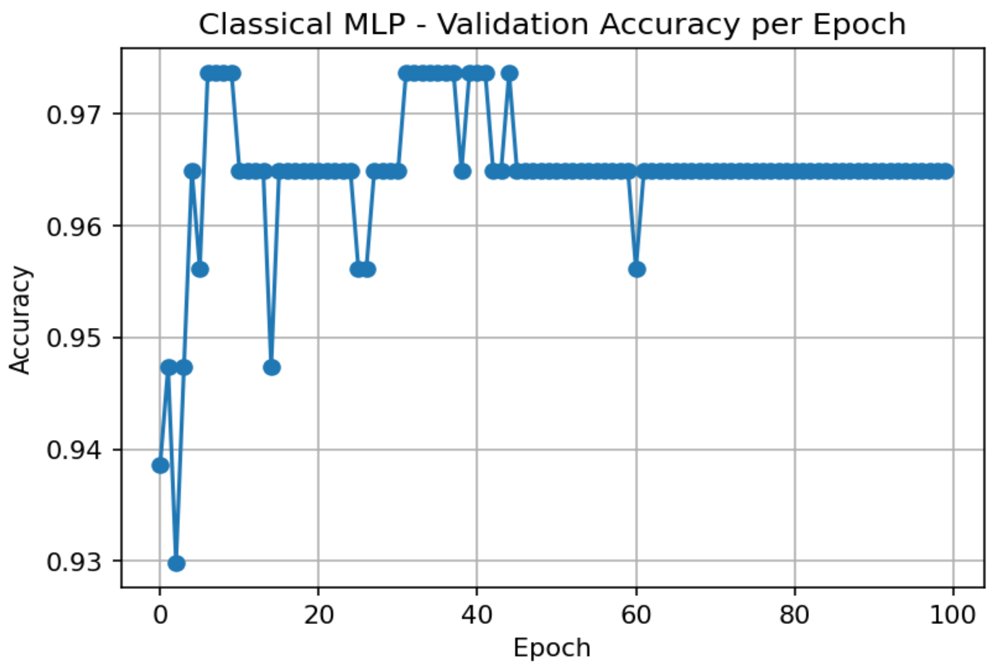

Figure 3

Validation F1

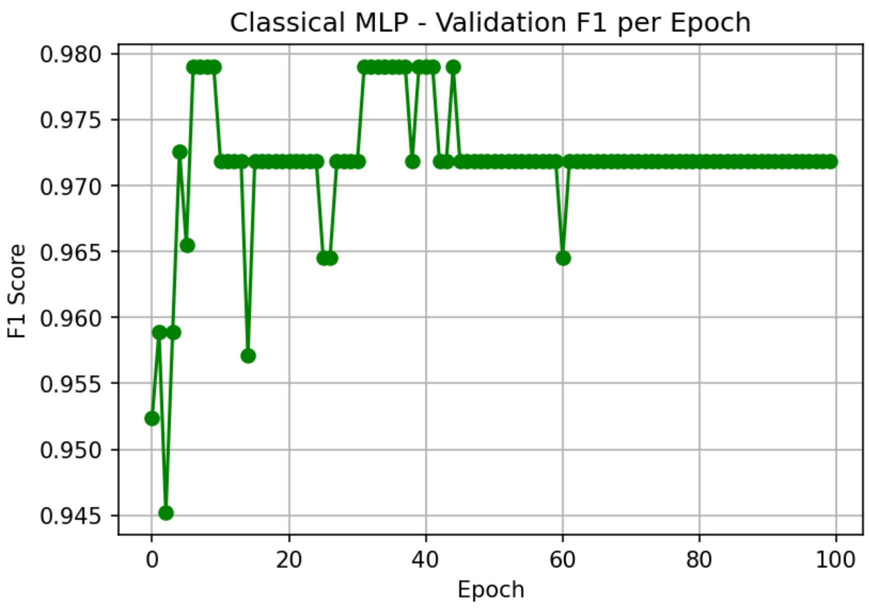

Figure 4

Precision – Recall

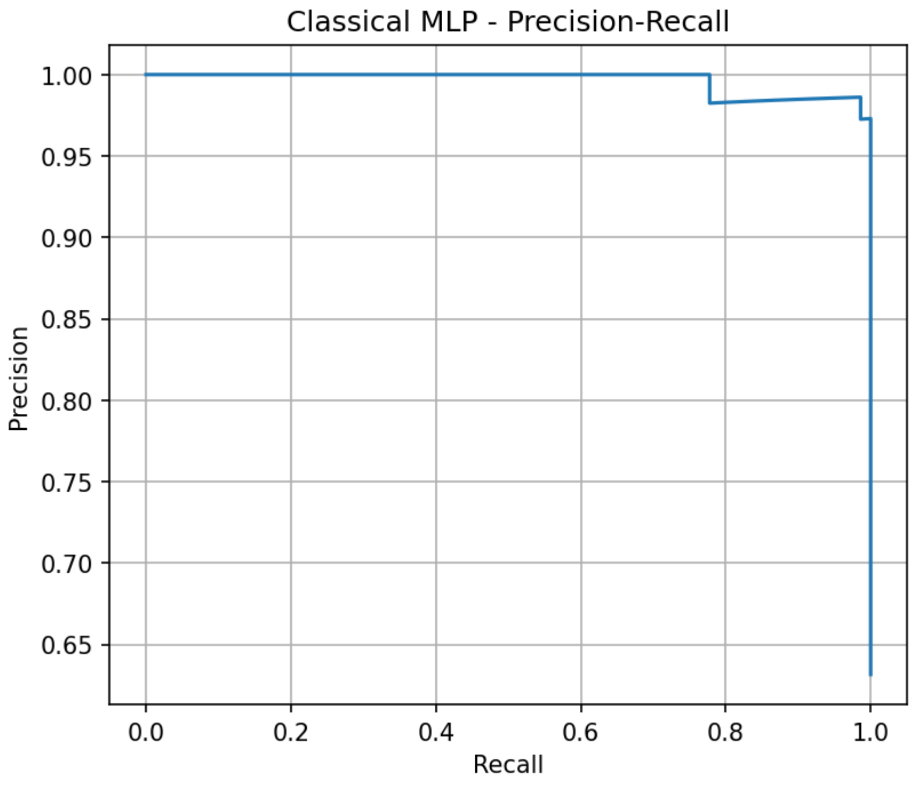

Figure 5

Predicted Probability Histogram

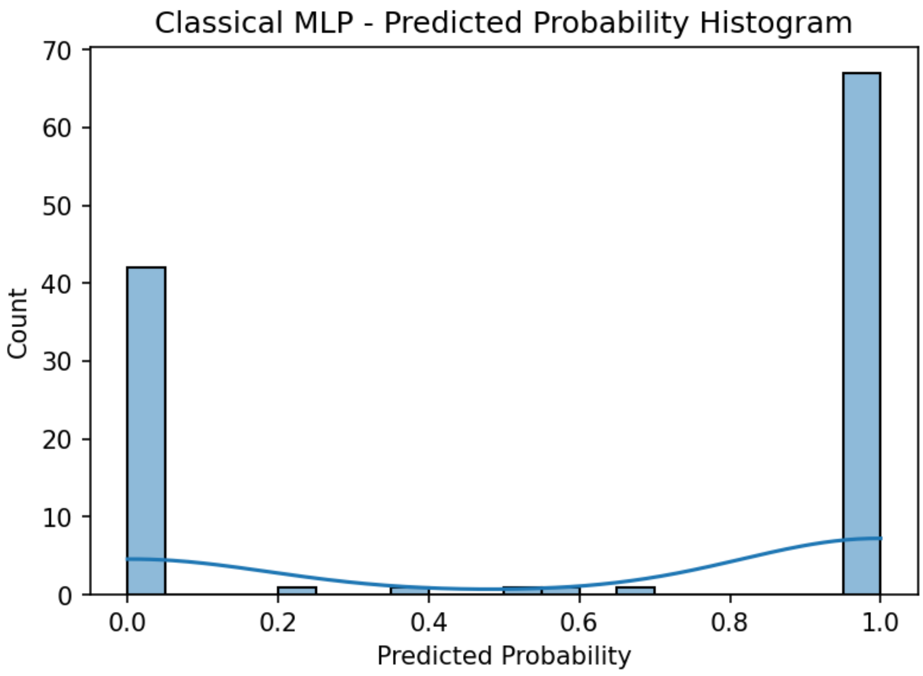

Figure 6

Calibration Curve

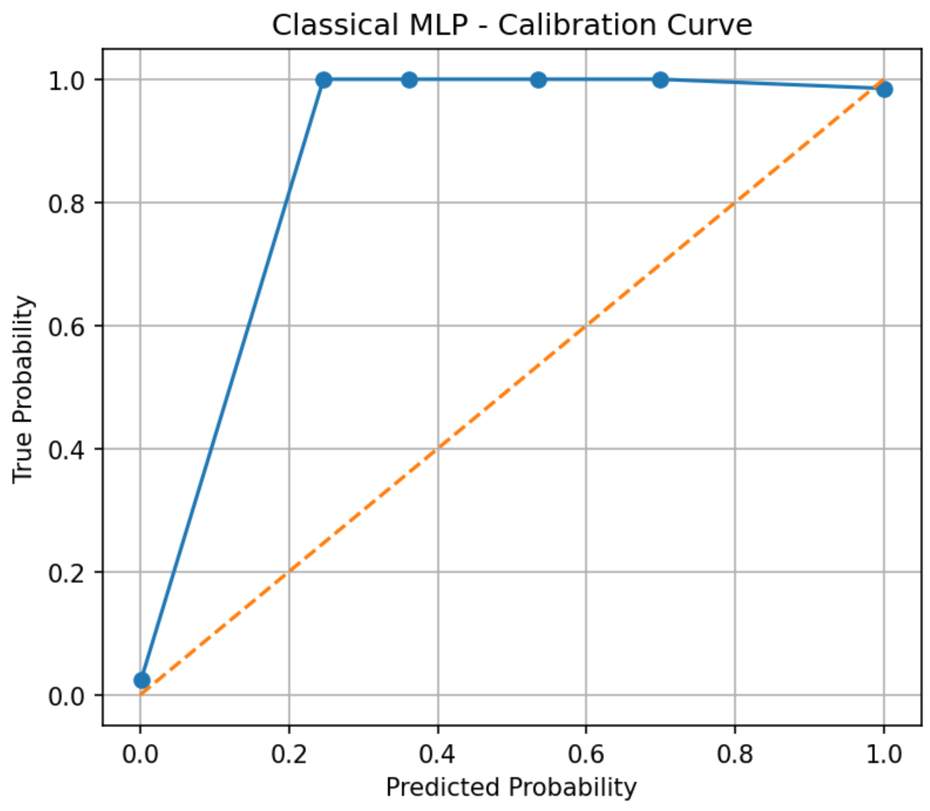

Figure 7

Confusion Matrix

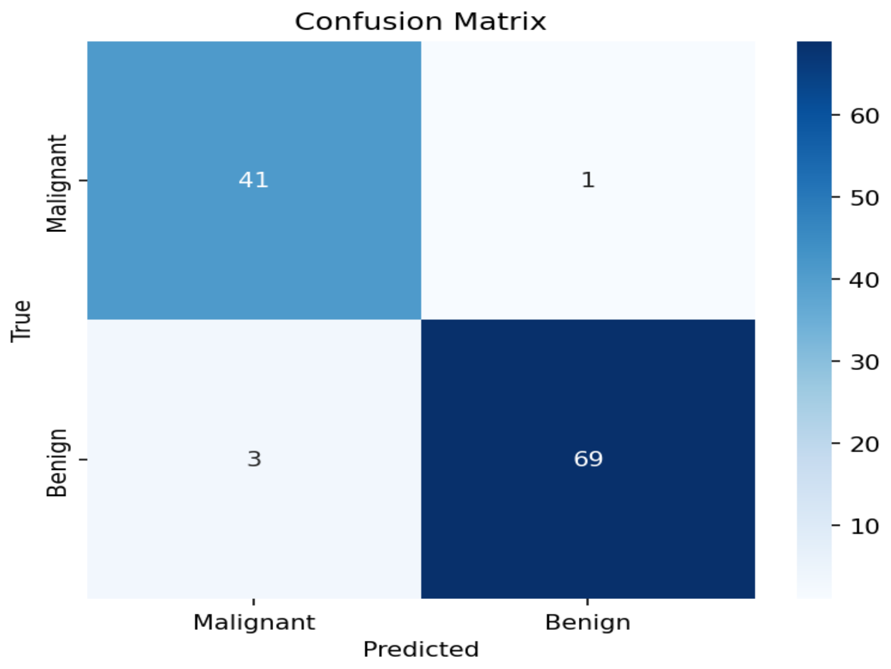

Figure 8

ROC Curve

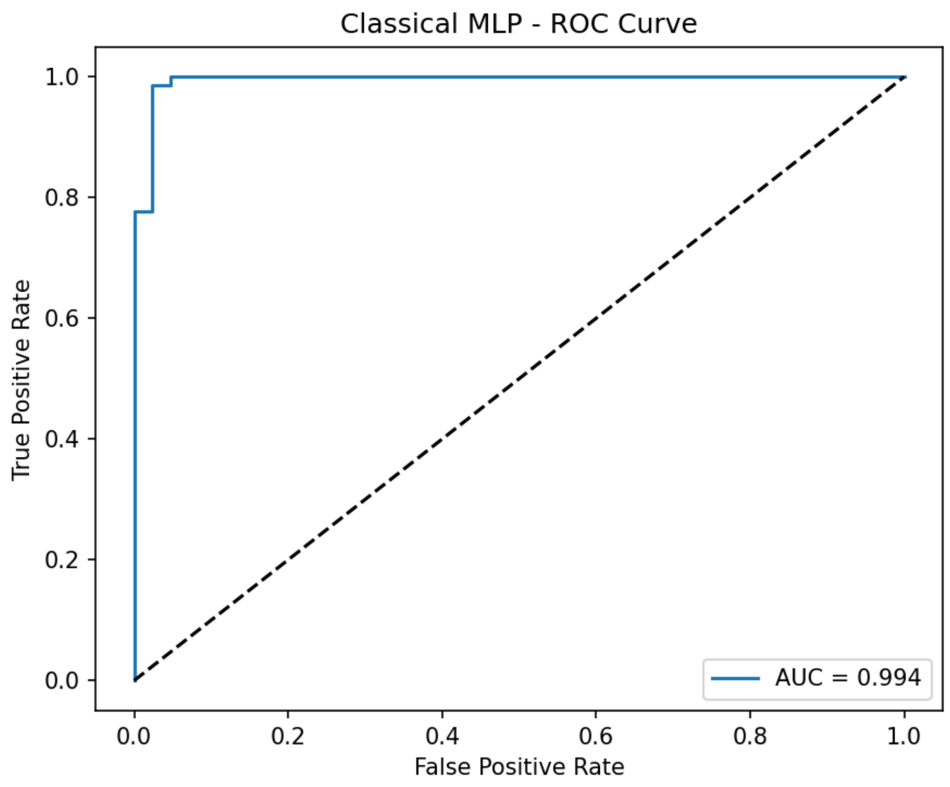

Figure 9

VQC Model - Model Architecture

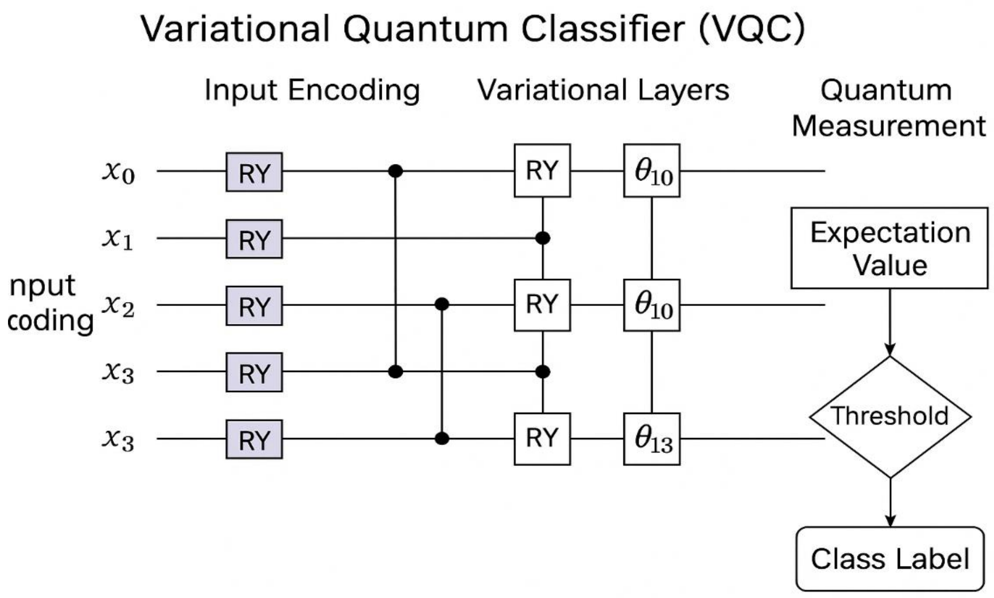

Figure 10

Loss Curve

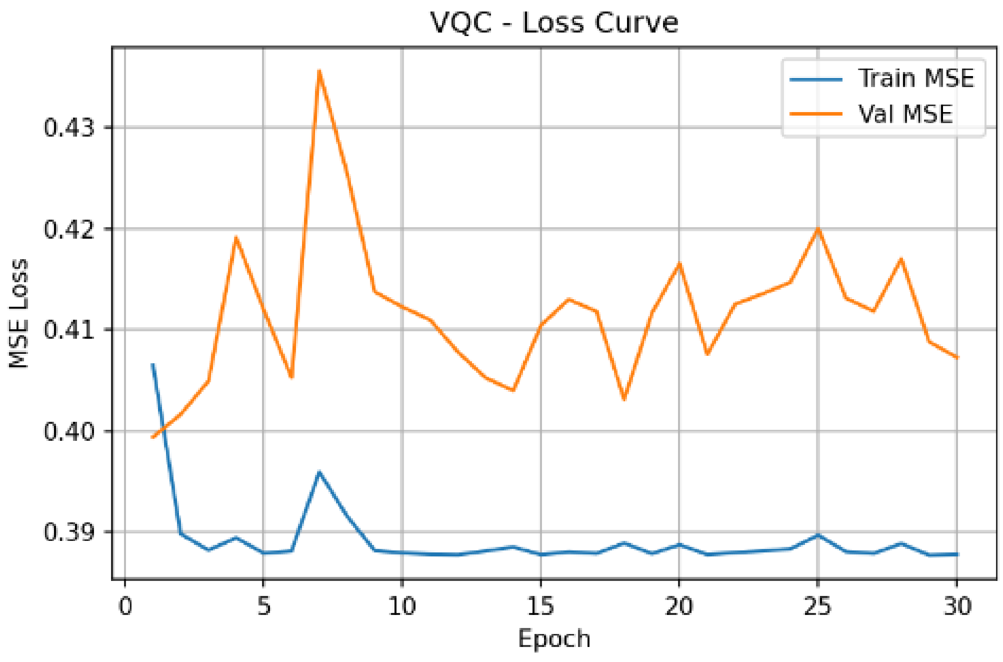

Figure 11

Validation Accuracy

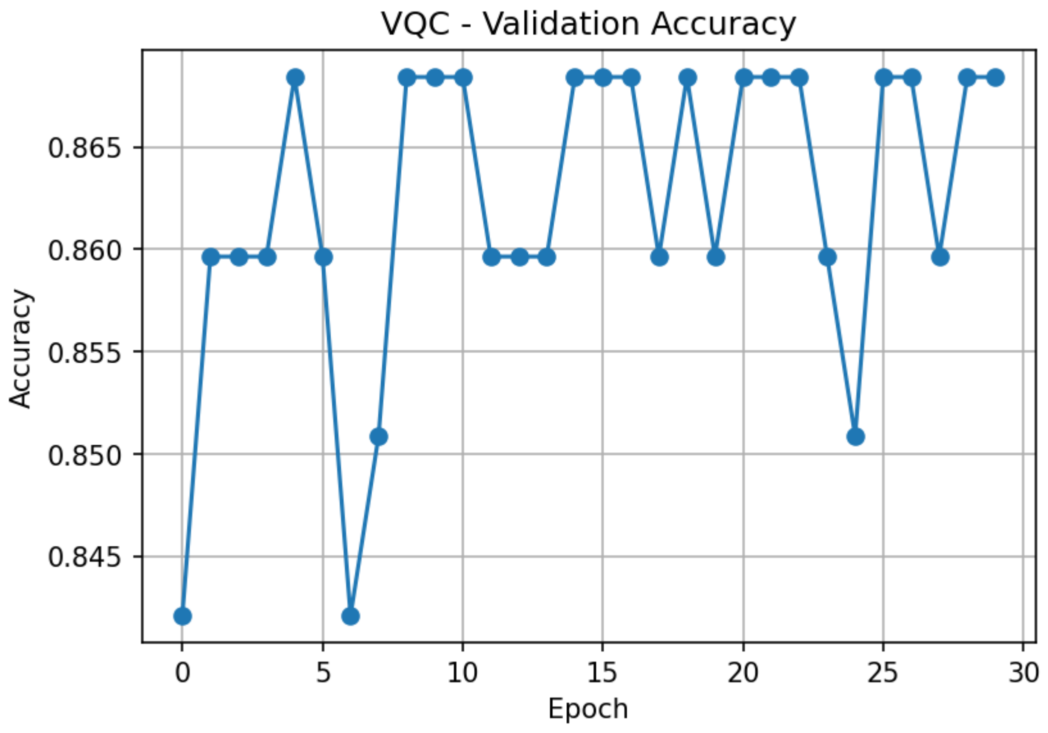

Figure 12

Validation F1

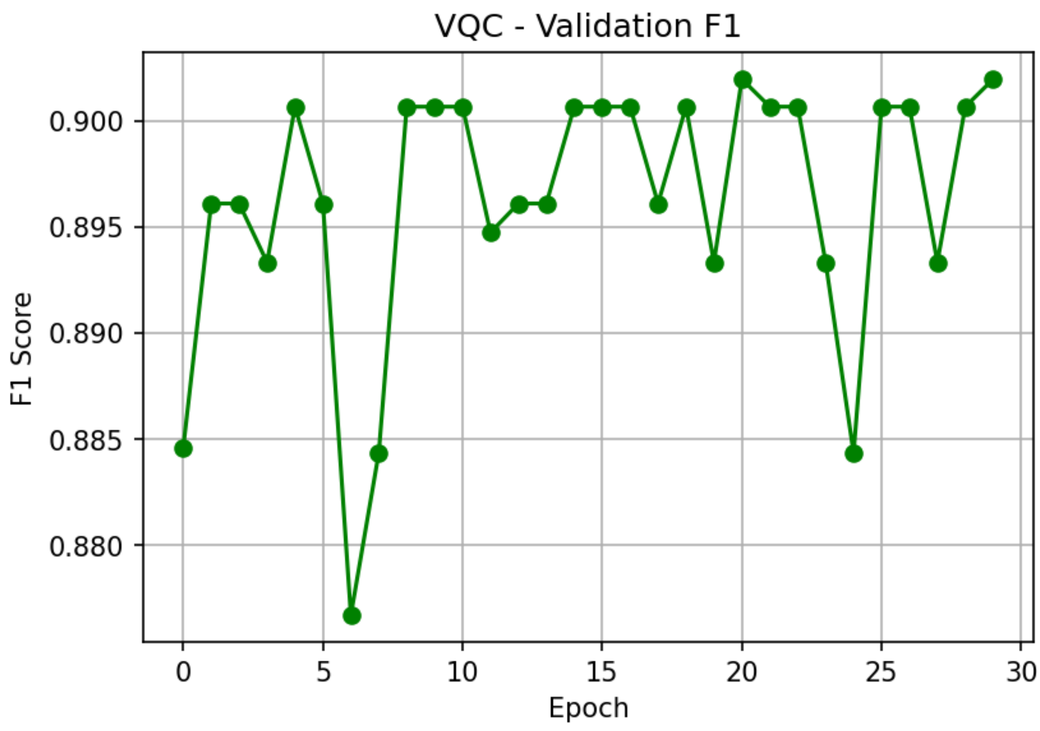

Figure 13

Precision – Recall

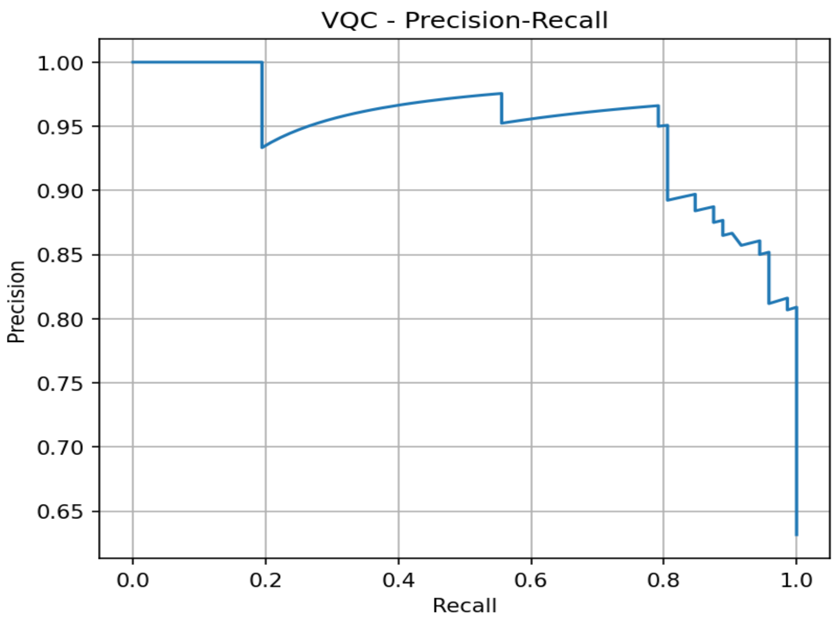

Figure 14

Prediction Probability Histogram

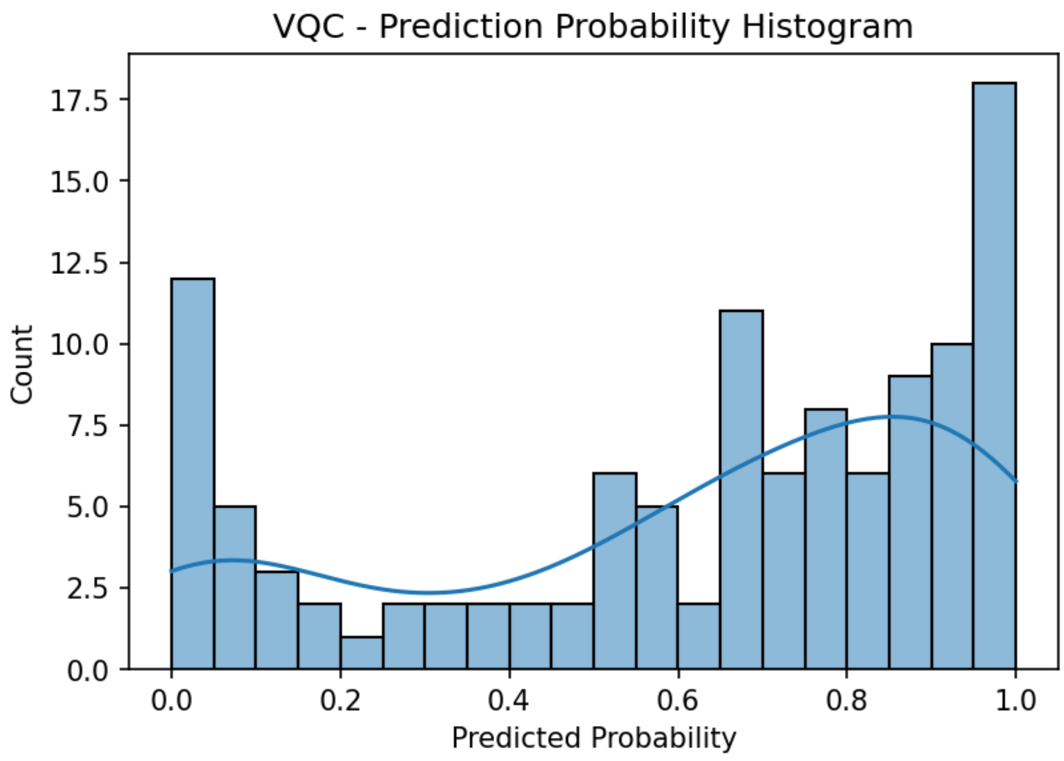

Figure 15

Calibration Curve

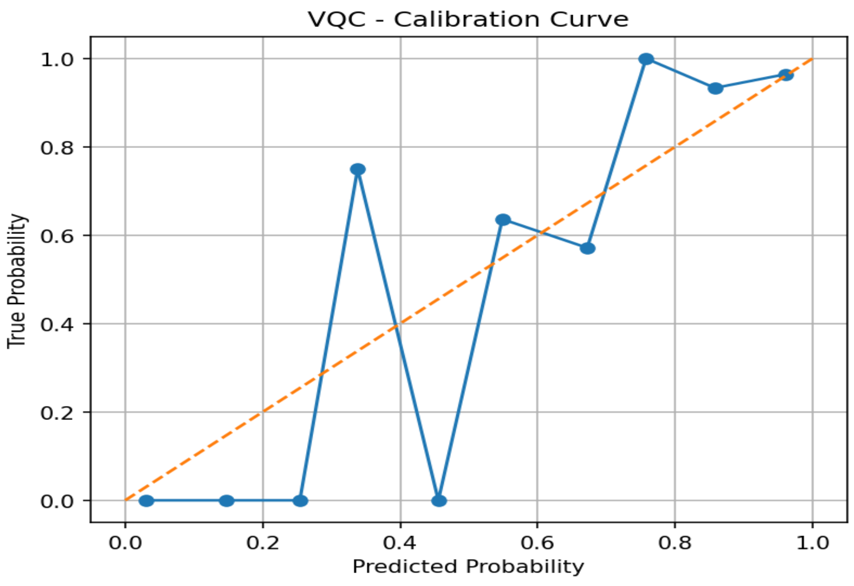

Figure 16

Confusion Matrix

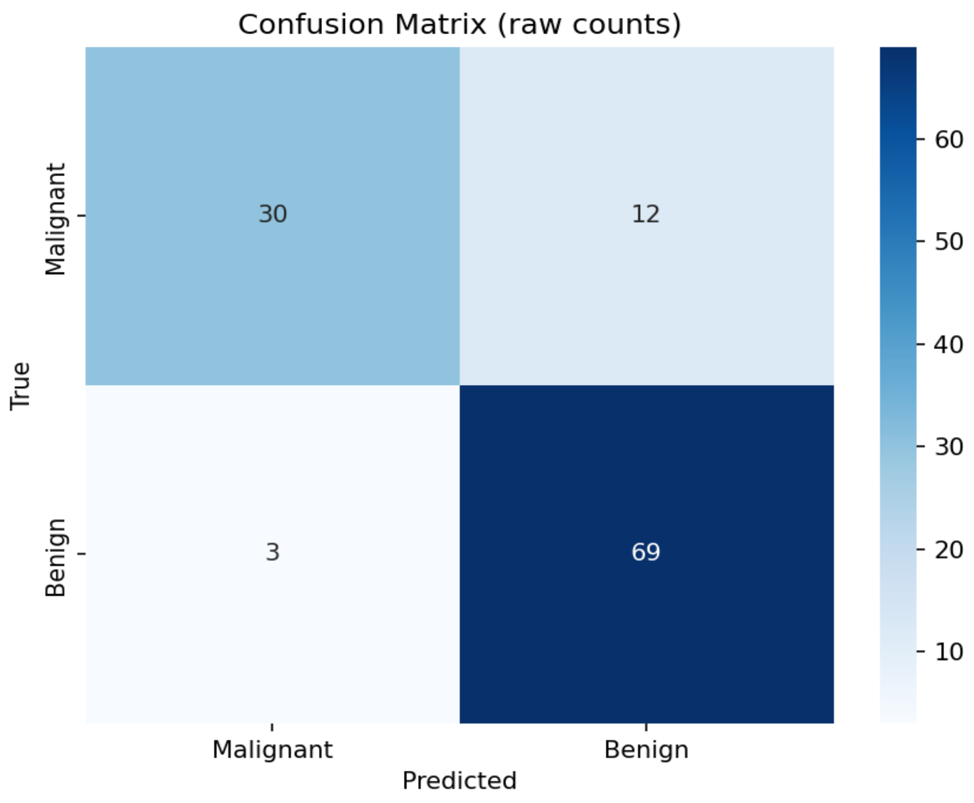

Figure 17

ROC Curve

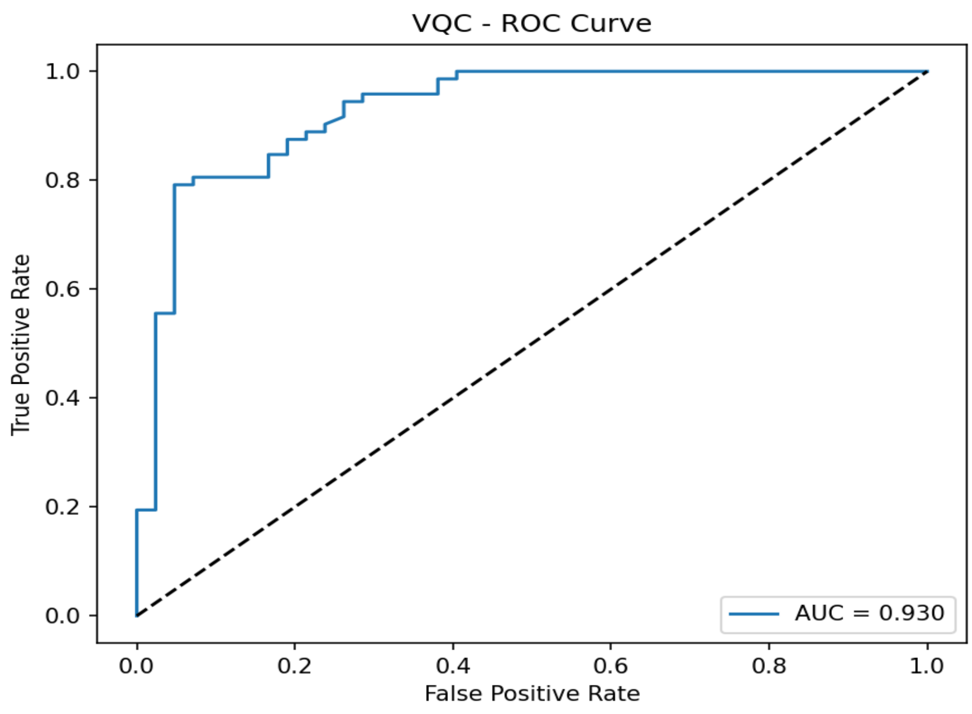

Figure 18

- **Hybrid Model**

Model Architecture

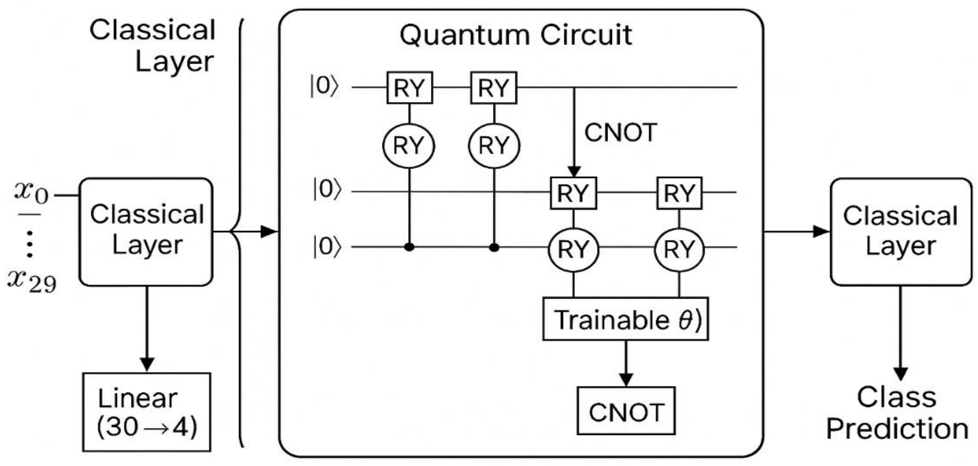

Figure 19

Loss Curve

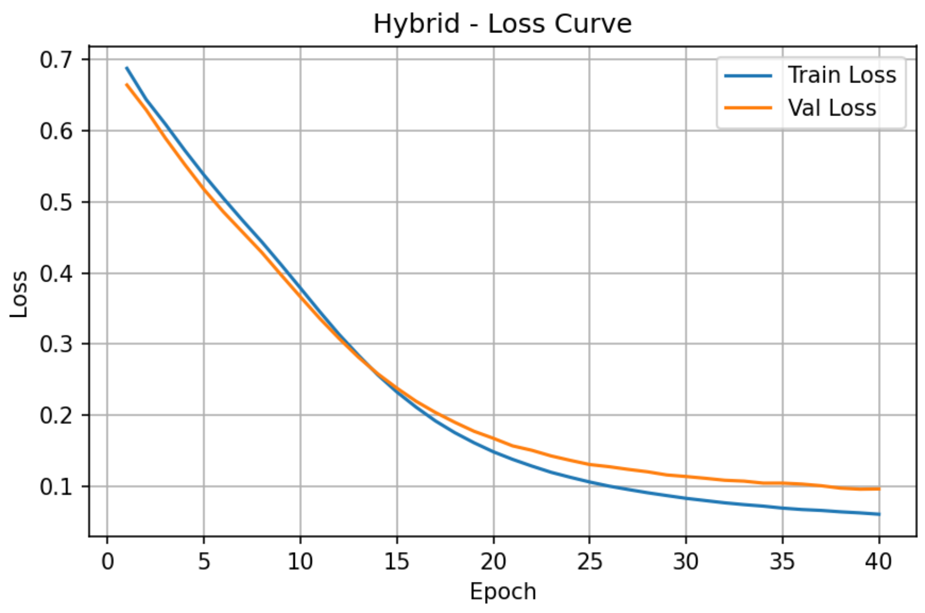

Figure 20

Validation Accuracy

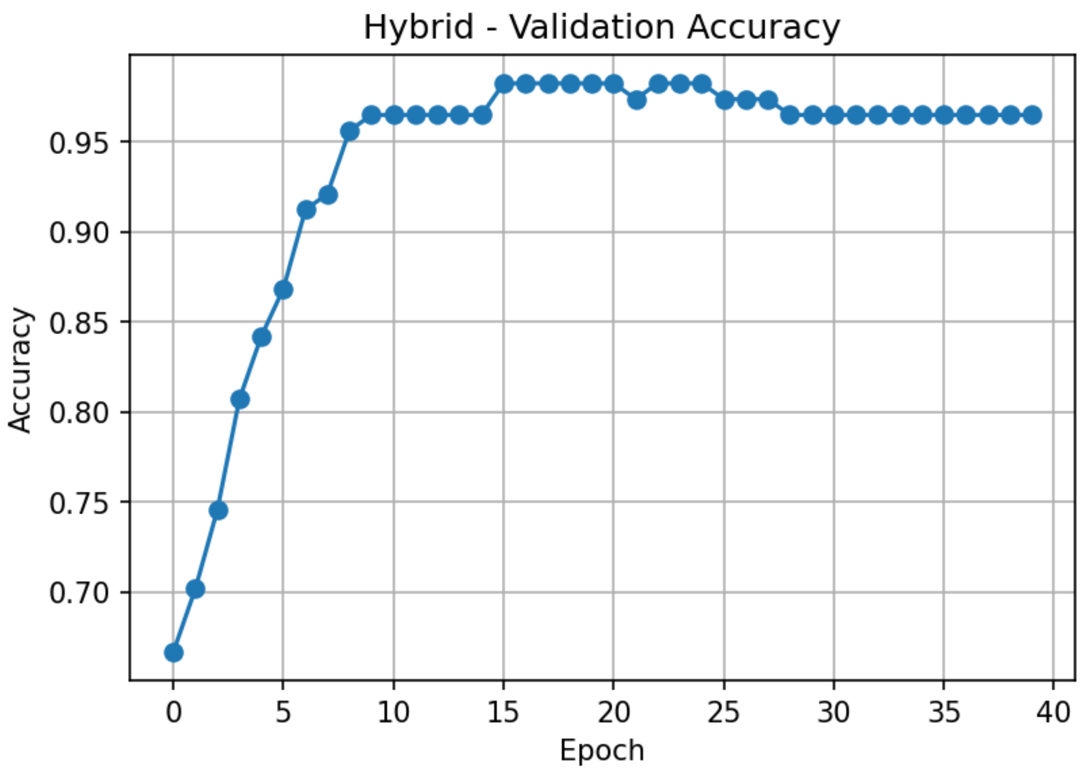

Figure 21

Validation F1

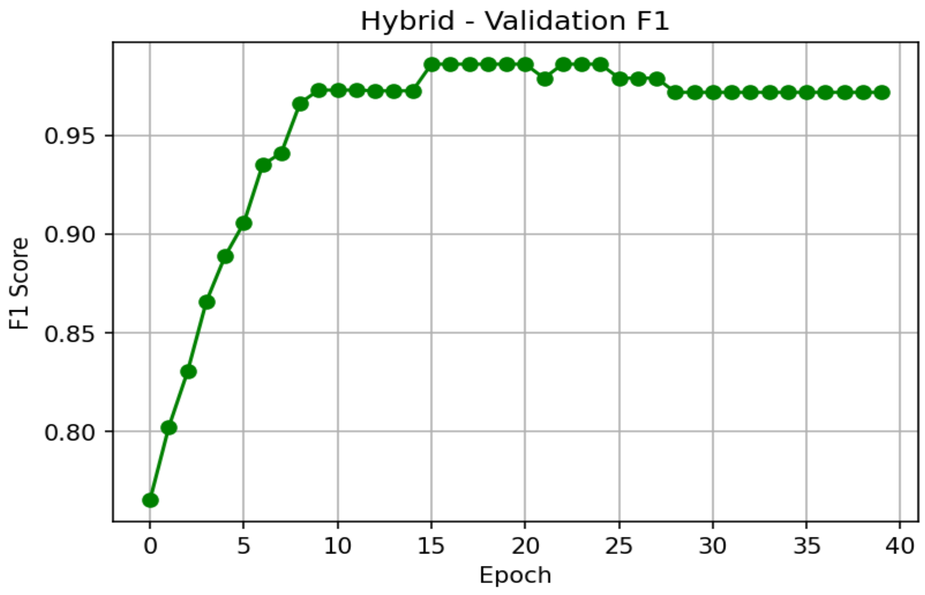

Figure 22

Precision – Recall

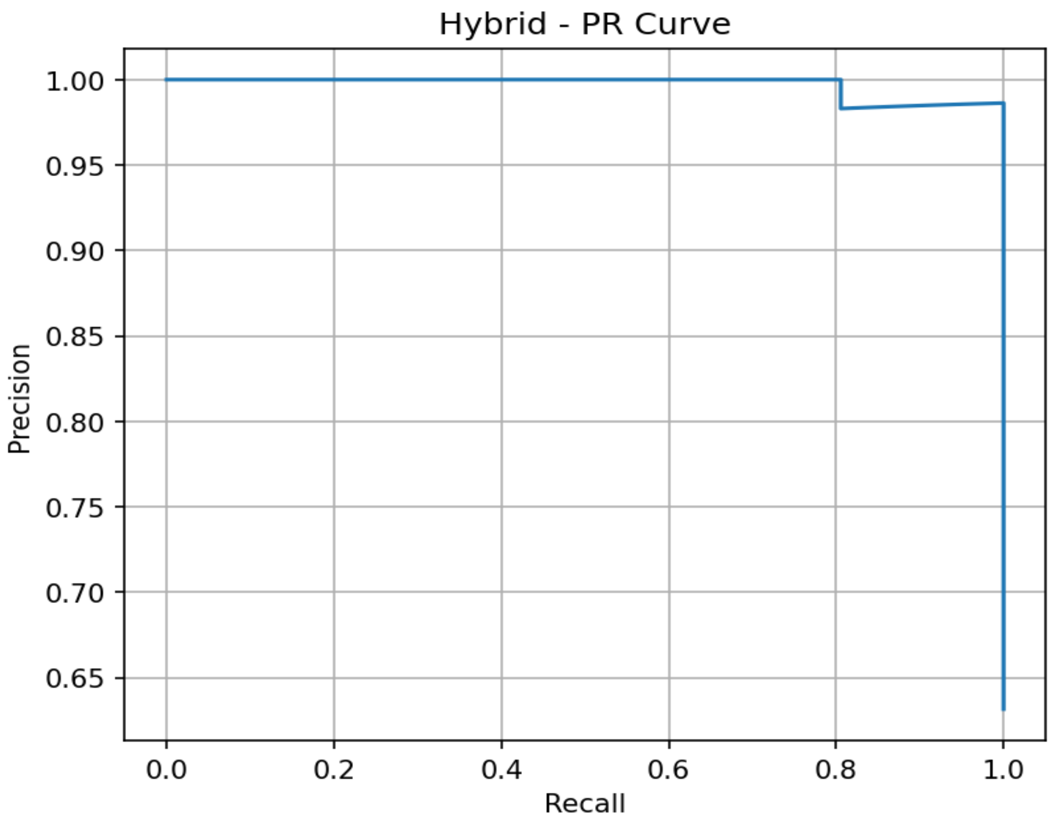

Figure 23

Probability Histogram

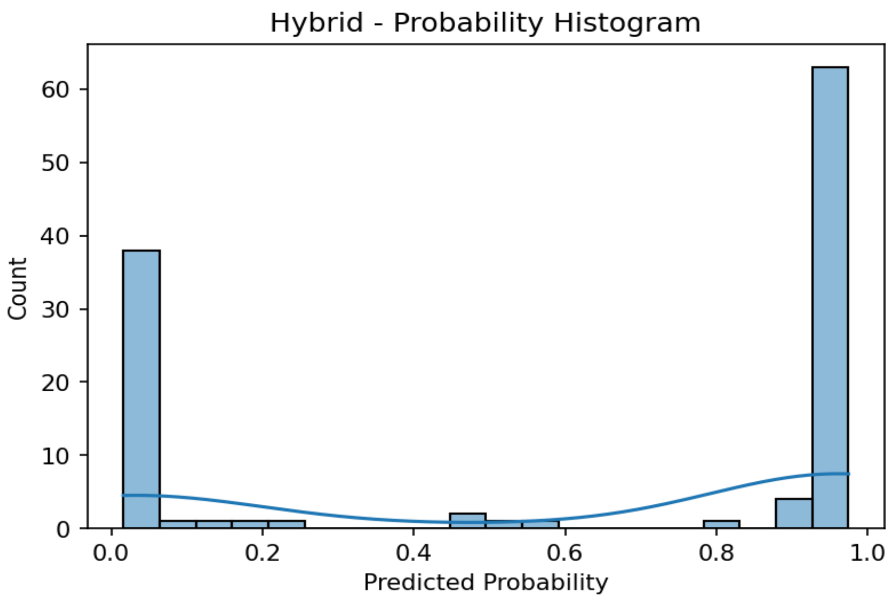

Figure 24

Calibration Curve

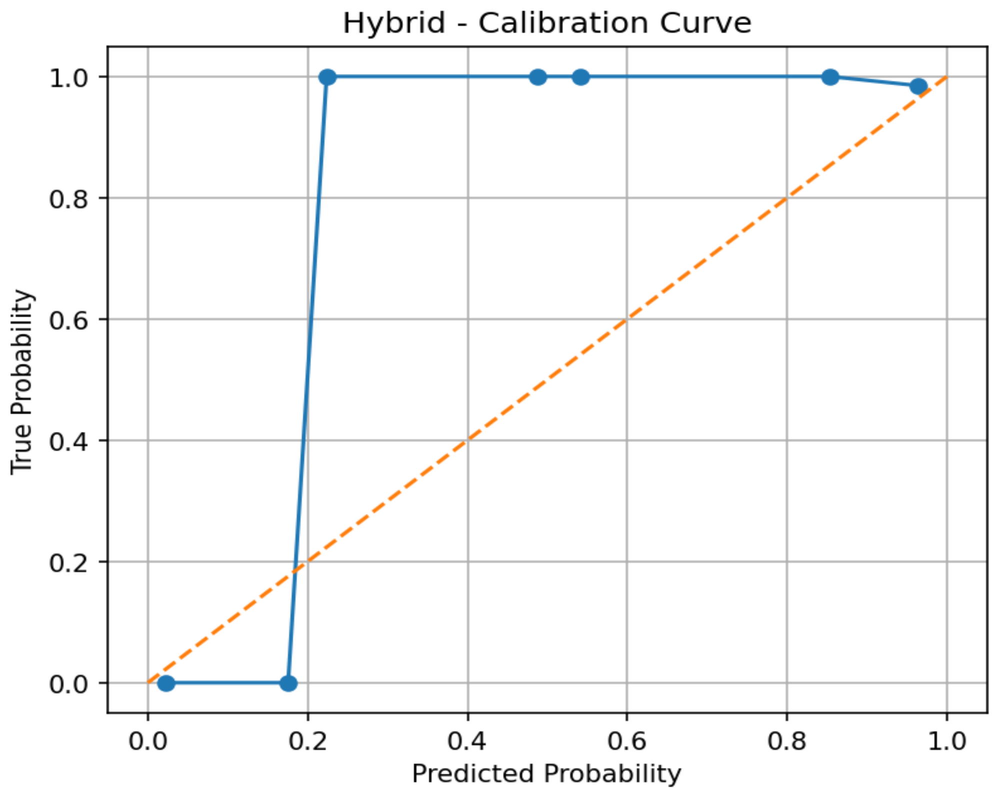

Figure 25

Confusion Matrix

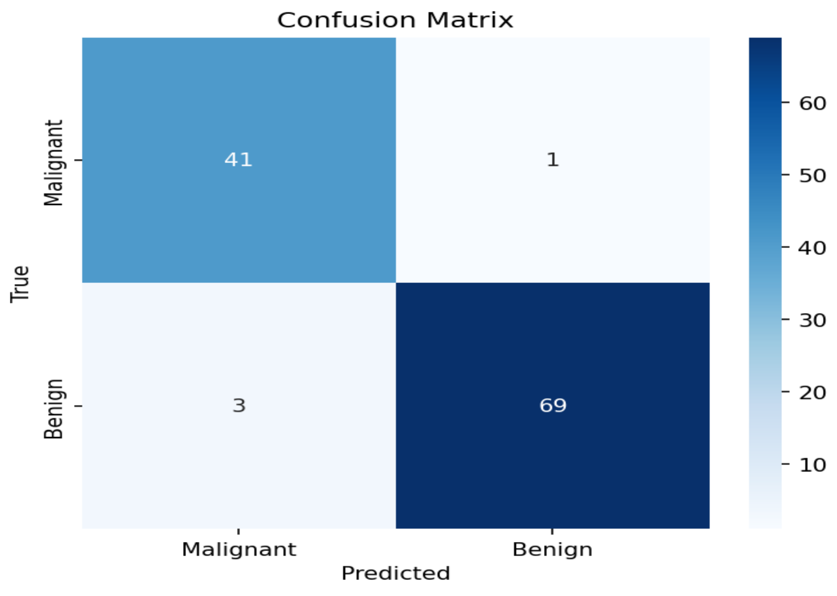

Figure 26

ROC Curve

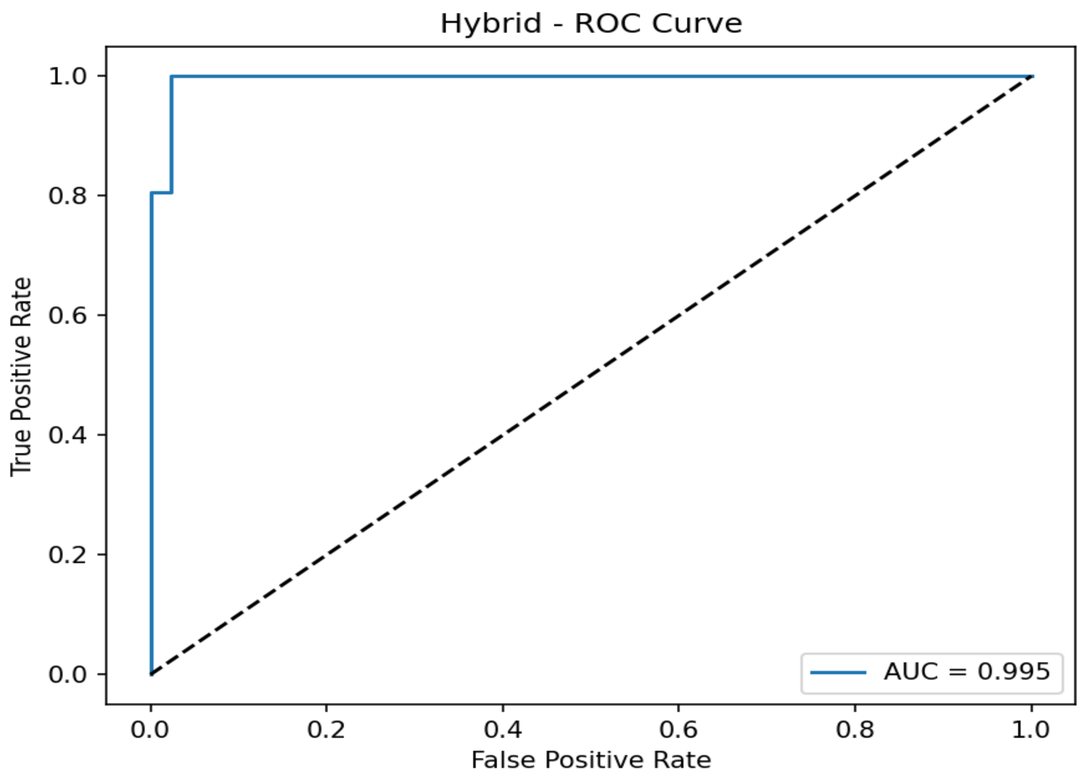

Figure 27

- **Model Comparison**

Performance Comparison

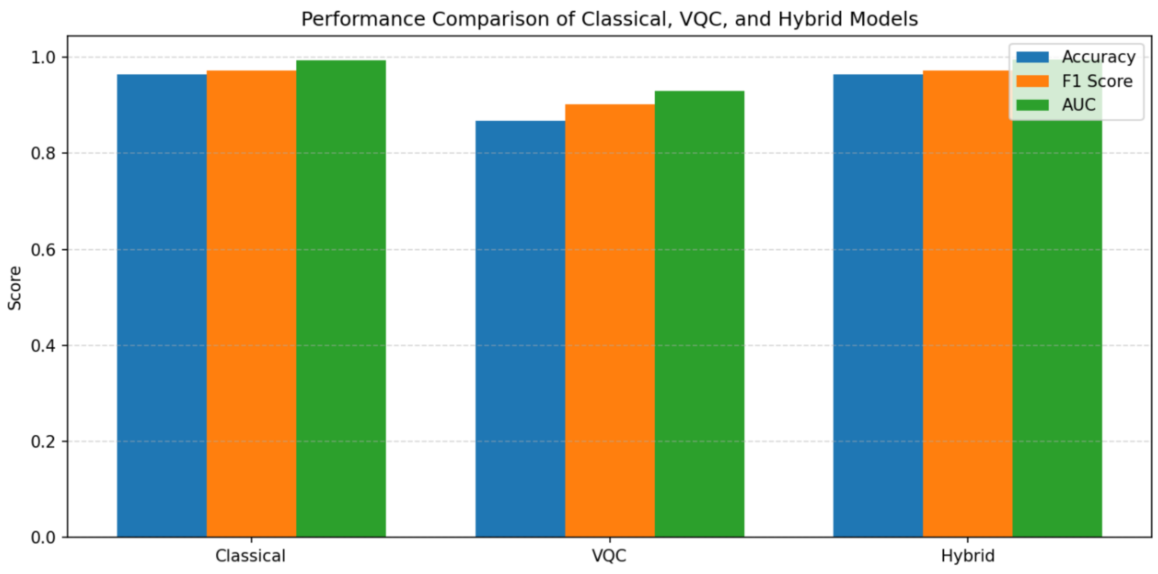

Figure 28

Radar Chart

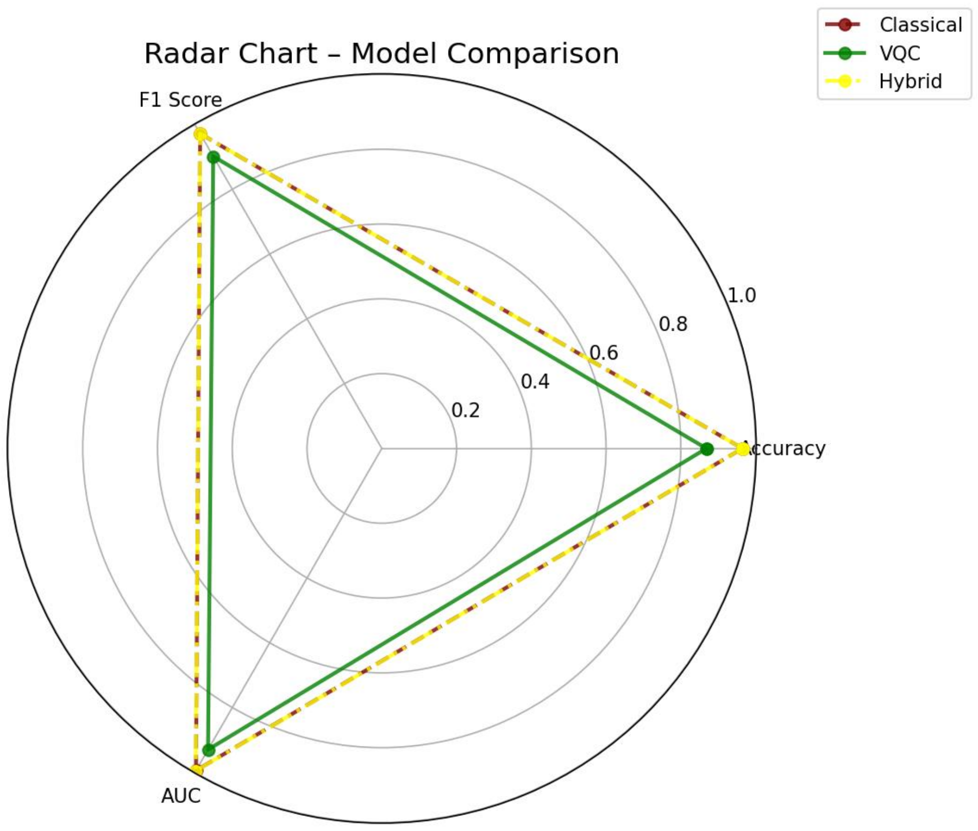

Figure 29

Model Performance

Table 2

Model	Accuracy (%)	F1 Score	ROC-AUC
Classical Neural Network	96.49	0.9718	0.9944
Variational Quantum Classifier (VQC)	86.84	0.9020	0.9297
Hybrid Quantum-Classical Model	96.49	0.9718	0.9954

7. RESULTS AND DISCUSSION

The tests used three ways to learn - regular neural network (MLP), a quantum-style classifier (VQC), along with a mix of both (HQC) - giving clear hints on how they differ when running, how fast they work, how well they tune themselves, also what results they predict. Here's a close look at how each one performs, settles down during training, uses resources, besides how easy it is to grasp their inner logic - with numbers backing up findings plus visuals helping show the story.

- **Overall Model Performance Summary**

The findings show each of the three models learned useful patterns from the Breast Cancer data - also managed decent binary predictions, though their speed and consistency differed. The traditional MLP stood out with top scores on every measure like accuracy, F1, and ROC-AUC; this highlights how dependable older neural networks can still be when working with organized medical information**.**

The Hybrid Quantum–Classical setup usually came in second, staying right behind the traditional one. Even with fewer settings and a simpler design, it still worked well - hinting at smart options for leaner but capable models ahead.

The VQC model had the worst performance numbers, showing shaky optimization behavior plus weak pattern handling on noisy mid-size hardware setups. Still, it managed to learn a bit - proof that small circuits with just four qubits and minimal layers can pick up differences between classes.

- **Model-wise Behavioral Interpretation**

Classical Neural Network

The classic MLP showed steady progress, barely wobbled in error rates, yet clearly told apart bad cases from good ones - visible in the confusion chart. Since the data's in tables, has just 30 columns, isn't time-based, this kind of model fits like a glove. Past studies back this up; deep nets tend to beat other models when data's clean and neatly organized because

- abundant trainable parameters,
- well-known activation functions,
- supercharged learning methods that tweak errors smartly,
- stable gradient flow.

This means the old-school MLP sets a high bar when you're comparing results.

Variational Quantum Classifier

The VQC model gave useful results - yet showed obvious drops in effectiveness when stacked against traditional networks because of:

- **Just 4 qubits handle 30 features -** creating a tight info squeeze**.**
- **Picks matter -** a bad start leads to flat zones or traps.
- **Updates jump around -** noise messes with tuning steps.
- **Gradients shift wildly -** not smooth, hard to follow. Squash data down a lot just to fit angles in.

On top of that, quantum circuits work differently than regular ones - they don't use flat geometry. Instead, they exist in a more complex setup called Hilbert space. So, info isn’t stored in weights; it’s held in wave-like states. That big shift makes them harder to understand right now. Yet, it also opens doors for way bigger computing power later on - if we get better hardware down the line.

The results weren't top-tier, yet they still prove the setup works - showing QML can function despite tight NISQ constraints through practical execution**.**

Hybrid Quantum–Classical Model

The hybrid approach showed solid results while beating the VQC. That suggests quantum boosts perform better with classical methods helping along instead of taking over completely. Advantages come through combining both techniques:

- Old-school data shrinking helps boost how fast quantum systems pack info.
- Quantum nonlinear state transformations, expanding feature expressiveness.
- Fully trainable from start to finish - this setup allows smooth learning without separate stages.

These setups seem more practical for upcoming AI tech, since hardware upgrades will happen step by step instead of jumping straight from old-school systems to full quantum ones.

- **Training Dynamics and Loss Trend Analysis**

How models learned changed a lot too:

Aspect	**Classical**	**VQC**	**Hybrid**
Loss curve	Smooth	Fluctuates	Moderately smooth
Convergence speed	Fast	Slow	Medium
Gradient stability	High	Low	Medium
Epoch requirement	Low	Higher	Moderate

The VQC's shaky curve comes from limits in quantum tuning - specifically barren plateaus - where slopes drop fast toward zero once the circuit gets deeper.

Hybrid results suggest leaning partly on traditional methods helps fix this problem - meaning gradient issues fade when standard nonlinear steps join in.

- **Resource, Complexity, and Efficiency Comparison**

Criteria	Classical	VQC	Hybrid
Trainable parameters	High	Very Low	Low
Memory requirements	Medium	Very Low	Medium
Compute backend	CPU/GPU	Quantum simulator	CPU + Quantum simulator
Practical deployability	Immediate	Future	Transitional
Adaptability	Flexible	Limited	Adaptive

The hybrid setup worked better overall, showing tomorrow's smart tech might mix regular with quantum instead of sticking to just one type.

- **Interpretation of Clinical and Real-World Implications**

Even though the data's meant for research, it still matters in real-world medicine - so how well the model works and how clear it is really counts. Right now, old-school models feel safer because they make steady choices when doctors need answers. Still, mix-ups of regular and quantum-style systems might catch up later

- better at pulling out key details,
- lower model complexity,
- stronger tuning when mixing different data types - like gene info, scans, or protein levels
- As tech improves, it grows without breaking a sweat.

So, mixing methods works better for real-world medical AI using quantum tech - instead of going all-in on pure quantum systems.

8. LIMITATIONS

This research comes with some limits worth noting. For starters, the quantum and mixed setups ran on a simulator instead of actual quantum gear - so real-life quirks like noise or signal loss might change outcomes. The test had few qubits and short circuits, possibly weakening how well the VQC and combined designs could perform. Just one tidy table-style dataset was tested, so results likely won't hold up for images, streams of time-based info, or blended data forms. On top of that, fine-tuning settings wasn’t pushed to its full potential across models, while tools explaining decisions were skipped - even though clarity matters in medical choices.

9. CONCLUSION

This study examined how well three machine learning methods worked - standard neural networks, a variational quantum classifier (VQC), and a mix of quantum and classical models - applied to breast cancer data from Wisconsin. By carefully building, testing, visualizing, and adjusting each system, results revealed the traditional network delivered top accuracy, steady outputs, quick convergence; meanwhile, the combined model came close despite using far less complexity, suggesting promise for leaner designs down the line. Although the VQC did manage pattern recognition tasks, its progress stalled more quickly, achieving weaker outcomes because today’s quantum devices struggle with precision and tuning limits, highlighting constraints typical in present-day noisy intermediate-scale setups.

The study finds classical models work best now for clear-cut medical sorting jobs. Yet hybrid setups offer a practical step forward into quantum-powered AI down the line. Quantum-only systems struggle right now - too few qubits, shallow circuits, tough tuning - but could improve when machines get better. So results show quantum ML isn't taking over classic methods yet; instead, it supports them. Over time, as tech advances, hybrid and full quantum approaches may take center stage

10. REFERENCES

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[3] Cerezo, M., Arrasmith, A., Babbush, R., Benjamin, S., Endo, S., Fujii, K., … Coles, Patrick. (2021). **“Variational Quantum Algorithms.”** *Nature Reviews Physics*, 3, 625-644.

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