

# Breast Cancer Diagnosis Using Hybrid Quantum-Classical Neural Networks

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**Abstract**—Accurate diagnosis of breast cancer is very essential. Machine learning is increasingly becoming the driver of cancer treatment. It has helped in the development of medical diagnostics. Quantum computational techniques have been discovered as a way of improving them even more. High data dimensionality tends to be restrictive since it is typically constrained. It reduces the effectiveness and functionality of classical models. Learning very distinguishable features in complex medical data set is also a major challenge. To address this, a quantum-classical neural network architecture has been suggested to enhance feature extraction. Traditional data preprocessing method, that is, principal component analysis has been combined with advanced circuits. Quantum methods have been merged with PCA. By using adaptive quantum layers, the model is good at representing multifaceted data patterns. A strong precision and memory performance in non-cancerous and cancerous is shown by this integrated model. This integrated model has preserved good performance across sample classifications.

It has an impressive accuracy rate of 96.49% on the Wisconsin Diagnostic Breast Cancer (WDBC) data when tested. The findings show the role of quantum-enhanced machine learning. Clinical decision-making can be enhanced and improved through learning, and early technologies of cancer detection can also be advanced.

**Index Terms**—Quantum machine learning, neural networks, classification of breast cancer, variational quantum circuits, hybrid computing, principal component analysis.

## I. INTRODUCTION

Breast cancer remains a leading cause of cancer-related mortality worldwide, representing 11.6% of all global cancer cases [1]. Proper diagnosis is essential as survival rates are low, and depends on early detection. Currently, clinical processes rely on radiological interpretation. But the manual procedure depends on the observer to observer and is liable to being missed subtle malignant patterns.

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Medical diagnostics has been opened with the help of machine learning. There are mechanisms to objectively analyze medical data. Classical machine learning (ML) models—such as Support Vector Machines (SVMs) [2] and Random Forests have shown considerable success in breast cancer classification tasks. However they are usually challenged with the non-linear, high-dimensional medical imaging datasets and deriving complex patterns out of them [3]. Recent works have been proven to implement hybrid quantum-classical architectures to eliminate such bottlenecks in other oncological areas, e.g., esophageal cancer typology. [4]. Naga Deep et al. (2025) suggested a quantum-enhanced. Convolutional neural network of breast cancer classification based on ResNet152, showing that it is about combining variational quantum circuits which can be translated into the feature extraction pipeline, can perform better in classification than solely classical. CNN baselines [5]. It is on this momentum that we venture. Quantum Machine Learning (QML) to deal with such problems.

We investigate Quantum Machine Learning (QML) to solve these issues. Quantum computing represents a paradigm shift in computational methodology, using superposition, entanglement and interference to process complex feature spaces more efficiently. Quantum machine learning (QML) offers potential advantages in pattern recognition, feature mapping, and optimization tasks by operating at the intersection of quantum computing and artificial intelligence [6], offering a diverse taxonomy of algorithmic approaches to solve complex problems [7].

Quantum computing has new ways for handling massive complexity. Rather than processing tasks sequentially like traditional systems, quantum systems use superposition and entanglement to represent exponentially large state spaces, using quantum interference to increase optimal solutions. In

this study, we rely on Variational Quantum Circuits (VQCs). VQCs function similarly to classical neural networks, learning by adjusting internal parameters via an optimizer. They are uniquely suited to capture the complex, non-linear patterns found in medical data. They offer an architecture for learning non-linear transformations that is similar to classical models, but with potentially greater expressivity for capturing the patterns found in medical data [8].

In this paper, a hybrid quantum-classical framework for breast cancer detection is presented. The contributions are as follows.

1) Hybrid Integration: A new hybrid architecture is introduced that combines strengths of classical preprocessing with quantum feature mapping.

2) Efficient Preprocessing: Principal Component Analysis (PCA) is used to reduce dimensionality without losing critical data and optimize the preprocessing pipeline.

3) Circuit Design: Circular entanglement is used by the quantum circuit to store non-linear patterns of data.

4) Strict Testing: The system performance has been checked with reference to the standard accuracy measures and feature. Analysis of importance has been carried out.

5) Clinical Viability: The potential of the framework has been undergone testing in clinical use.

## II. MATERIALS AND METHODS

### A. Dataset Description

The Wisconsin Diagnostic Breast Cancer (WDBC) data has been used for evaluation [9]. It has 569 samples in total. A digitized features 30 numerical features are calculated from an image of a Fine Needle Aspirate (FNA) of each sample. The features contain different types of measurements of each cell nucleus: radius, texture, perimeter, area, smoothness, compactness, concavity, concave points, symmetry and fractal dimension.

### B. Data Preprocessing Pipeline

In order to ensure data quality and consistency, the preprocessing pipeline starts with data cleaning procedures. The patient ID column is removed as it provides no diagnostic information. The diagnosis labels undergo binary encoding: malignant cases are encoded as 1, and benign cases as 0. Data splitting uses stratified sampling to maintain the original class distribution across training and testing sets using an 80-20 split.

The feature scaling is an important preprocessing step, especially with quantum circuits that are sensitive to input magnitudes. Normalization is done by StandardScaler only during training. data, and the learned parameters are then used to test data to prevent data leakage. Features are scaled by the scaling process.

$$X_{scaled} = \frac{X - \mu_{train}}{\sigma_{train}} \quad (1)$$

where  $\mu_{train}$  and  $\sigma_{train}$  denote training set statistics.

The main purpose of PCA is to adapt the high-dimensional classical simulations to the limits of existing quantum devices, a strategy that has just proved to be very successful in compressing medical features for quantum neural networks [10]. Preprocessing has been structured in a manner to match strictly with the 10-qubit circuit architecture. The input vectors have been narrowed down to 10 main features out of 30 raw feature parts to fit this hardware limit. Efficiency has been balanced with accuracy via this transformation. 95.21% of the cumulative variance is retained while effectively removing noise.

### C. Quantum Circuit Architecture

The circuit has been implemented using PennyLane's default.qubit simulator [6]. To match the output of the PCA step, the device is configured with 10 qubits. To load the data, angle embedding is used; this technique maps the classical features directly onto the rotation angles of the quantum gates:

$$|\psi\rangle = \prod_i R_Y(\theta_i)|0\rangle \quad (2)$$

We constructed the variational layers using trainable rotation gates, specifically RX, RY, and RZ. We implemented circular CNOT gates to handle the entanglement operations between these layers. This arrangement ensures full connectivity; it allows all qubits to participate in quantum correlations before we measure the final Pauli-Z expectation values:

$$\text{CNOT}(q_0, q_1), \text{CNOT}(q_1, q_2), \dots, \text{CNOT}(q_9, q_0) \quad (3)$$

### D. Hybrid Model Architecture

In order to successfully connect the classical and quantum components, we created the hybrid architecture. Batch normalization and dropout regularization are used to stabilize the initial inputs. We use dense layers with ReLU activation after the parameterized quantum processing; the binary classification is produced in this last step using a sigmoid readout.

The training procedure is guided by binary cross-entropy loss:

$$L = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})] \quad (4)$$

To ensure stability, we chose the Adam optimizer and combined it with adaptive learning rate scheduling. We used a batch size of 16 and a hard cutoff of 50 epochs for the training phase. We put stability first by enforcing early stopping, which immediately reduces overfitting by ending the training loop if validation loss ceases to improve.

## III. RESULTS AND DISCUSSION

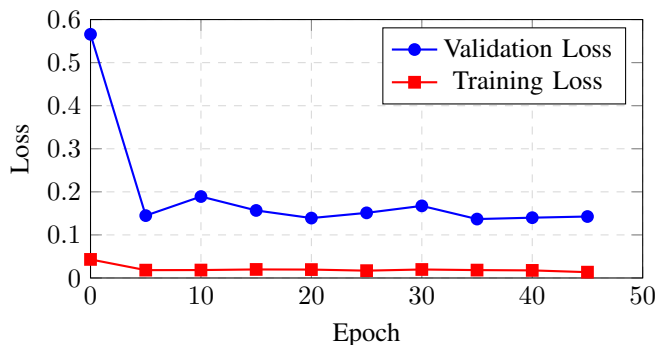
The hybrid quantum-classical model achieves a final test accuracy of 96.49%. Table I shows the detailed classification performance metrics.

As the results indicate, the two classes demonstrate great performance, where especially high recall (98%) is achievable with malignant cases, decreasing false negative.

Table I: Classification Performance Metrics

Class	Precision	Recall	F1-Score	Support
Benign (0)	0.99	0.96	0.97	72
Malignant (1)	0.93	0.98	0.95	42
<b>Accuracy</b>	0.96			114
<b>Macro Avg</b>	0.96	0.97	0.96	114
<b>Weighted Avg</b>	0.97	0.96	0.97	114

Training Convergence



Accuracy Progression

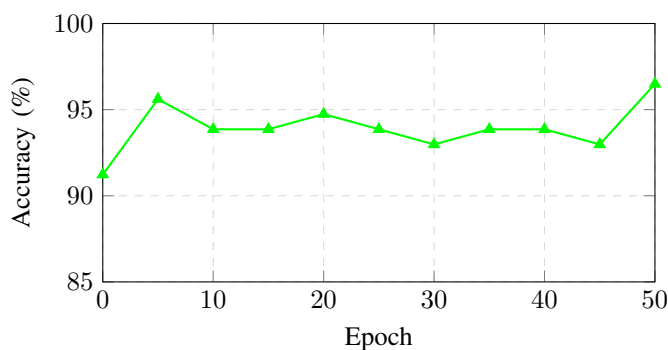


Fig. 1: Training performance: (a) Loss convergence showing stable training without overfitting; (b) Validation accuracy progression reaching 96.49% at final epoch

This is an important consideration in diagnosing cancer. The confusion matrix has high diagnostic capability and a single false negative case, a false negative rate of 2.4% which is good in comparison with clinical standards.

#### A. Training Performance and Convergence

Training converges gradually after 50 or so epochs, and validation accuracy improving with training accuracy and no overfitting. The corresponding loss and accuracy trends are illustrated in Fig. 1.

Consistent performance is demonstrated by multiple training runs with different random seeds, with standard deviation across runs remaining below 1%, confirming results which are duplicable. The best performance of the model is achieved at epoch 50 with minimal validation loss.

Top Feature Importance Scores

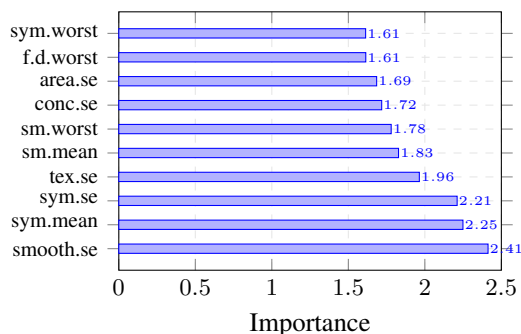


Fig. 2: Abbreviated feature importance: smooth=smoothness, sym=symmetry, tex=texture, sm=smoothness, conc=concavity, f.d=fractal dimension

Confusion Matrix

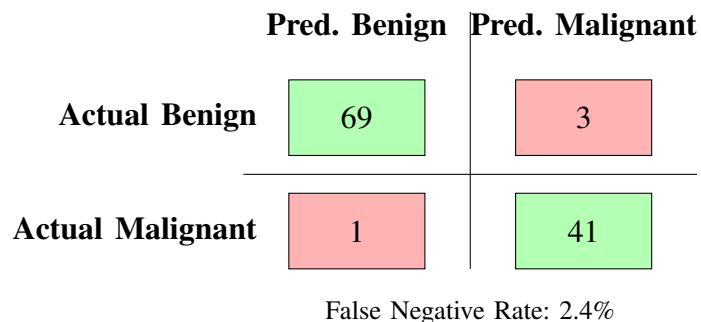


Fig. 3: Confusion matrix showing diagnostic performance. Green: correct classifications, Red: errors

#### B. Feature Importance Analysis

Some important patterns in feature contributions is revealed by principal component analysis. The top 10 most important features identified through PCA is visualized in Fig. 2.

The top features include smoothness\_se (2.413), symmetry\_mean (2.249), symmetry\_se (2.211), texture\_se (1.964), and smoothness\_mean (1.828). Texture and smoothness features dominate the rankings, with standard error measurements providing significant diagnostic value. It is observed that these feature rankings are directly related to established pathology. The malignancy analysis demonstrates an abnormal texture and diminished smoothness as its main indicators.

#### C. Confusion Matrix Visualization

The classification is visualized in Fig. 3 with performance, which emphasizes the ability of the model.

There is a good diagnostic picture of the data. Only one false negative is registered under the malignant samples. This translates to 2.4% error rate, a margin that is deemed as acceptable because of high clinical cost of missed diagnoses. In terms of raw counts, the model correctly flagged 41 of

42 malignant samples (97.6%); in benign cases, it had 69. accurate predictions out of 72 (95.8%).

#### D. Quantum Advantage Considerations

This has been considered as a variational quantum simulation problem. The benefit in this case is that the model can understand highly complex data, rather than just high computing speed. Circular entanglement is applied to produce certain quantum correlations. This circuit enables the circuit to map relationships between features which are not classical linear algebra. The quantum states are in a high dimensional Hilbert space, so a solution landscape may be searched by the much richer circuit than a typical neural network weight space. A standard neural network is used to run a control experiment.

The quantum hardware performance gains are the specific gains in performance. This is allowed to pinpoint by this baseline. A classical neural network is designed with an identical topology (10 inputs, two hidden layers); it is, however, topped out at 93.86% accuracy. This performance difference validates the particular lift offered by the quantum processing layer.

#### E. Clinical Implications

Since the precision and recall measures are well balanced, we advise the use of this as a supplementary diagnosis help in secondary reading. Where few resources are available, this robotic examination might frontload the routine cases, empowering the radiologists to focus their expertise on more challenging pathological findings. Yet still we ought to recognize the occurrence of one false negative result; while the 2.4% error level exceeds the conventional range of variability of 4-10 percent. Any unidentified case of cancer in a human being, that is not detected is a vital safety issue that requires further consideration and protective measures. We will use this model in the situation when we are working on it.

During preliminary screening stage. With automation of the initial assessment, we project a possible 30-40% decrease in reduced workload of radiologists and retained diagnostic accuracy.

In the future we will aim at improving the input parameters through incorporation of mammographic imaging, which is an area where Convolutional Neural Networks that are quantum-integrated have been recently had much promise [11], and medical history, which would enhance the diagnostic framework in general.

#### F. Limitations and Future Work

We admit that the WDBC data is a limited one and homogeneous representation of patients. To establish clinical practicability, verification with bigger, multi-institutional datasets is necessary to have. Also because our experiments were conducted using simulation, evaluation on actual quantum computing hardware is an important next step. It is a crucial phase to determine the effects of environmental noise on qubit stability.

The stretching of this framework creates major hardware challenges and obstacle; to support more feature sets, you need

more complex. circuits that push the boundaries of existing NISQ technology. We hope that advanced error correction methods will be required to cope with the increased effects of decoherence. We would like to examine federated quantum machine learning; this methodology would enable healthcare institutions to come up with models but retains full privacy of patient information in their respective places.

#### IV. CONCLUSION

The possibilities of hybrid quantum-classical networks to diagnosis of breast cancer is discussed. After carefully tuning WDBC dataset has been used to achieve a test accuracy of 96.49% with data preparation and circuit settings. This result implies that quantum-enhanced models are getting competent enough to match normal classical approaches to medical work.

These results draw attention to a couple of aspects. Classical quantum has been effectively used together with noise reduction feature mapping. The model also showed good stability by finding a balance between accuracy and recall without merely memorising the training data. Finally, this work suggests that variational. quantum algorithms are prepared to get valuable insights out of. actual medical datasets.

In the future, we will execute these models on physical quantum processors, instead of simulators. This step is required to obtain the impact of hardware noise on the results. We also intend to test the model with records of several medical centers; this shall determine whether the system is capable of dealing with various patient groups effectively.

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