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A Quantum Convolutional Neural Network for Breast Cancer Classification using Boruta and GA-Based Feature Selection with Quantum Feature Maps

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Abstract **Accurate and computationally efficient classification systems are essential for the early detection of breast cancer, particularly when dealing with complex and high-dimensional medical datasets. Traditional machine learning models often face limitations in capturing intricate nonlinear relationships inherent in such data, potentially compromising diagnostic performance. In this study, we introduce QBG-QCNN, a Quantum-enhanced framework named Boruta-GA optimized Quantum Convolutional Neural Network, designed for breast cancer classification. The model is trained on the Breast Cancer Wisconsin (Diagnostic) Dataset, which contains 30 numerical features extracted from fine needle aspiration (FNA) images of breast tissue samples. To reduce dimensionality while preserving critical diagnostic information, a hybrid Boruta-GA feature selection strategy is applied to extract key features such as radius_mean, texture_mean, area_mean, and concavity_mean. These selected features are then encoded into a 4-qubit quantum circuit using advanced quantum feature maps ZZFeatureMap, RealAmplitudes, and EfficientSU2, eliminating the need for manual feature engineering. The encoded quantum data is processed through a QCNN that incorporates quantum convolution, pooling, and parameterized ansatz layers, leveraging quantum entanglement and parallelism for more efficient learning. Implemented using PennyLane and IBM Qiskit, and optimized with the COBYLA, the model achieves outstanding performance: 94.3% accuracy, 95.2% precision, 94.6% recall, and a 93.0% F1-score. These results significantly outperform those of classical CNNs, standard QNNs, and other hybrid models. In conclusion, QBG-QCNN demonstrates that quantum machine learning, when integrated with intelligent feature selection, offers a powerful, scalable, and interpretable solution for early-stage breast cancer diagnosis. Future research will extend this framework to multi-modal datasets and real-device deployment on real quantum devices under noise constraints.**

Keywords Quantum Convolutional Neural Network (QCNN), Boruta, Genetic Algorithm (GA), Quantum Feature Maps, Breast Cancer Classification, Feature Selection, Quantum Machine Learning.

I. Introduction

Breast cancer is the most common type of cancer affecting women, and remains one of the leading causes of cancer-related deaths worldwide [1]. When treatment starts early, more than 90% of patients can survive the disease [2]. However, because the data in medical imaging can be very complicated and extensive, current classification methods often struggle to separate benign from malignant tumors accurately. Typical machine learning models can have difficulties with extracting data features and commonly miss the smaller, nonlinear links among the many elements. Consequently, their results are less reliable,

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highlighting the need for more robust and efficient classification approaches [3].

QML has emerged as a promising alternative to classical ML for breast cancer classification [4]. Quantum algorithms can process large amounts of data efficiently du due to quantum phenomena such as entanglement and superposition, offering potential speedups over classical approaches [5]. Quantum algorithms like Quantum Support Vector Machines (QSVM) [6], Quantum k-Nearest Neighbors (QkNN) [7], Quantum Random Forest (QRF) [8], and Quantum Decision Trees (QDT) [9] have been shown to reduce computational load and improve classification accuracy [10]. These algorithms can process and predict complex datasets faster and more accurately with quantum speedup. Limited quantum hardware exists because noisy intermediate-scale quantum (NISQ) devices are being developed. Early quantum classifier studies suggest QML models may outperform traditional models in complex medical applications despite hardware constraints [11].

Quantum Convolutional Neural Networks (QCNNs) have shown particular promise for breast cancer classification, addressing several of the limitations inherent in classical ML models [12]. High-dimensional medical datasets challenge CNN computational efficiency and feature extraction. In contrast, QCNNs utilize quantum superposition and entanglement to accelerate data processing and effectively capture complex nonlinear patterns, thereby enhancing classification performance. These quantum models not only improve processing speed—crucial for real-time medical diagnostics—but also scale efficiently for large datasets.. Whale Optimization Algorithm [13] and Quantum Genetic Algorithm [14] optimize feature selection and computational efficiency, making QCNNs ideal for large-scale medical classification. QCNNs represent a scalable and forward-looking solution for advancing healthcare applications.

Although quantum classifiers show considerable promise, most current approaches either underexplored advanced feature selection methods or lack integration with end-to-end quantum-enhanced convolutional pipelines. Classical feature selection methods alone may be insufficient for achieving robust classification, while unoptimized quantum models may not scale well for real-world, large-scale medical applications. Therefore, a hybrid approach combining advanced feature selection and quantum convolutional processing is underexplored. Integrating classical optimization techniques, such as evolutionary algorithms or swarm intelligence, with quantum circuits can significantly improve feature relevance and qubit efficiency. Moreover, constructing scalable and noise-resilient quantum-classical architectures is essential to bridge the gap between experimental success and clinical deployment.

This study introduces a Quantum Convolutional Neural Network (QCNN) enhanced by Boruta [13] and Genetic Algorithm (GA) [14] for robust feature selection to classify breast cancer. In the proposed QBG-QCNN model, quantum circuits encode optimized feature sets into qubits using ZZFeatureMap, RealAmplitudes, and EfficientSU2. These advanced quantum feature maps enable the model to capture complex, non-linear data relationships by converting selected features into quantum states . After that, quantum convolutional and pooling layers in the QCNN architecture perform spatial and quantum transformations on the encoded data, like classical layers, but with the computational advantage of quantum processing. This study aims to improve breast cancer diagnosis, particularly in distinguishing between benign and malignant tumors. Traditional CNN-based models are often more computationally intensive and less diagnostically effective than the hybrid Boruta and GA method for feature selection. This quantum feature extraction and processing method is validated by quantum simulations of the model's accuracy, precision, recall, and F1-score. The performance of the QBG-QCNN model is assessed using a 4-qubits configuration. In order to optimize model performance, the IBM Qiskit framework-implemented QBG-QCNN model trains with quantum-enhanced features and uses advanced quantum speedup and hyperparameter tuning. These integrative methods outperform classical methods, with the QBG-QCNN using RealAmplitudes scoring 94.3% accuracy, 95.2% precision, 94.6% recall, and 93.0% F1-score. The choice of quantum feature map significantly affects model performance, with RealAmplitudes consistently outperforming other feature maps.

This research aims to develop a quantum-enhanced hybrid deep learning model that accurately classifies breast cancer using an optimized feature set and QCNN architecture, surpassing classical models in terms of accuracy, computational efficiency, and scalability, especially in distinguishing benign from malignant tumors. The key contributions of the research are as follows.

1. Integration of Boruta and Genetic Algorithm (GA) ensures robust feature selection by combining exhaustive screening and dimensionality reduction.
2. Adopt the advanced quantum feature maps (RealAmplitudes, ZZFeatureMap, EfficientSU2) which enhances nonlinear relationship modeling in high-dimensional data.
3. Deployment of the QCNN architecture enables spatial data transformation with quantum computational benefits, improving classification accuracy.
4. Empirical evaluation using IBM Qiskit shows that the proposed model, especially with RealAmplitudes, achieves 94.3% accuracy, 95.2%

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precision, 94.6% recall, and 93.0% F1-score, outperforming classical baselines.

Below is the outline for the remainder of the article. Section 2 presents a review of related literature; Section 3 describes the proposed methodology; Section 4 shows the results of the experimental evaluations of the system's performance; and Section 5 concludes the study.

II. Literature Review

During the last few years, advancements in computer science have significantly contributed to the evolution of QML . Since data is rising 20% each year, effective data management is required [15]. QML is becoming an increasingly important part of the neural network field. Its ability to solve problems that regular computers cannot handle has attracted researchers and experts from all over the globe.

Although [15] worked with pictures by rasterizing them through QML, [16] revealed the benefits of QML in data analysis. As presented in [17], QML could impact the future of AI. QNNs have helped move this field forward. QNNs use qubits that can be superposed, giving the ability to improve the processing capacity in some applications [18,19]. Quantum neural networks are better than CNNs in capturing quantum data, how fast they learn, and F1-score, recall, accuracy, and precision.

Since there are not enough qubits and NISQ devices, researchers are investigating the hybrid QBG-QCNN as an alternative interface. Dimensional reduction was achieved in this model by applying a quantum evolutionary neural network or a traditional method, and then a quantum neural network was applied [21]. Using a quantum-classical neuron model, predictions can be made for commodity prices [22]. [23], In that study, HEP data were examined with a hybrid quantum-graph convolutional neural network. It shows that hybrid QNNs are flexible in their application. People found that our hybrid quantum model performed better than CNNs when tested with classical adversarial images [24].

Traditional options have less storage and processing power than QNN. Over the past six years, QNN architectures have undergone rapid transformation. History will cover implementation methods, quantum circuit models, and challenges. In Part 1, "The Implementation Technique," VQA and other theoretical frameworks and processes for building QNN models are introduced. QBM, QCVNN, and other quantum circuit QNN models are covered in part 2. The article's conclusion addresses today's biggest issues. Though new, this area has magical and practical potential. [25]. ML and DL improve breast cancer diagnosis and prediction. [26]. Used the Wisconsin Breast Cancer Dataset to predict breast cancer. Data exploration, Label Encoder, and Normalizer pre-processing were used before model creation, and several machine-learning approaches were evaluated with 96% success. These methods used Random Forest and SVM. Additionally, an ANN model reached 99% accuracy, while a CNN model achieved 97% accuracy , demonstrating the continued promise of both classical and hybrid approaches in this domain.

Another study suggested quantum neural networks could detect cancer [27]. Using the Breast Cancer Wisconsin (Diagnostic) dataset and a QNN, they classified cancer cells as benign or malignant. CNNs with less computing power are less accurate than QNNs. Finally, research [28] suggested a quantum-classical hybrid machine-learning picture categorization. MNIST evaluated a conventional SVM with quantum feature maps and kernels. Traditional machine learning was less accurate and resource-intensive than hybrid. The study found that ML and QML can detect and predict breast cancer, and that quantum computing may improve machine learning.

Early diagnosis helps treat many diseases. Doctors manually examine MRI scans to diagnose cancer. To provide the best care, doctors may double- and triple-check diagnoses. Brain tumor detection requires a two-layer hybrid quantum convolutional neural network (HQCNN). We got 94% accuracy with this model [29]. Breast cancer is one of the deadliest female diseases, so early detection is crucial. ML may detect diseases faster and more easily than traditional methods. New technologies produce high-dimensional cancer and healthcare data. Feature selection can fix these classification issues. This study suggests optimizing the Decision Tree's Breast Cancer dataset categorization with WOA [31]. The results are 92.26% accurate compared to the norm [30].

In addition, deep learning (DL) has become a key focus in the fields of pattern recognition and image processing . We will use DL to integrate many imaging modalities for clinical practice and diagnostic imaging. Three-year trend: pixel-level image fusion. This study offers a new medical diagnosis method by fusing image modalities. Image fusion is strongest when informative. CNNs enhanced the quantum-behaved particle swarm optimization (QPSO) algorithm for multimodal medical image integration [32]. In another research [33], the authors presented four key contributions: (1) it proposed a novel hybrid model, QKSVM, integrating Binary Harris Hawks Optimization (BHHO) with Quantum Kernel SVM for effective gene selection and cancer classification; (2) it applied Principal Component Analysis (PCA) to reduce gene dimensionality for compatibility with limited quantum qubits; (3) it evaluated performance on Colon and Breast microarray datasets, achieving up to 94% **accuracy**; and (4) it benchmarked various quantum feature maps (ZFeatureMap, ZZFeatureMap,

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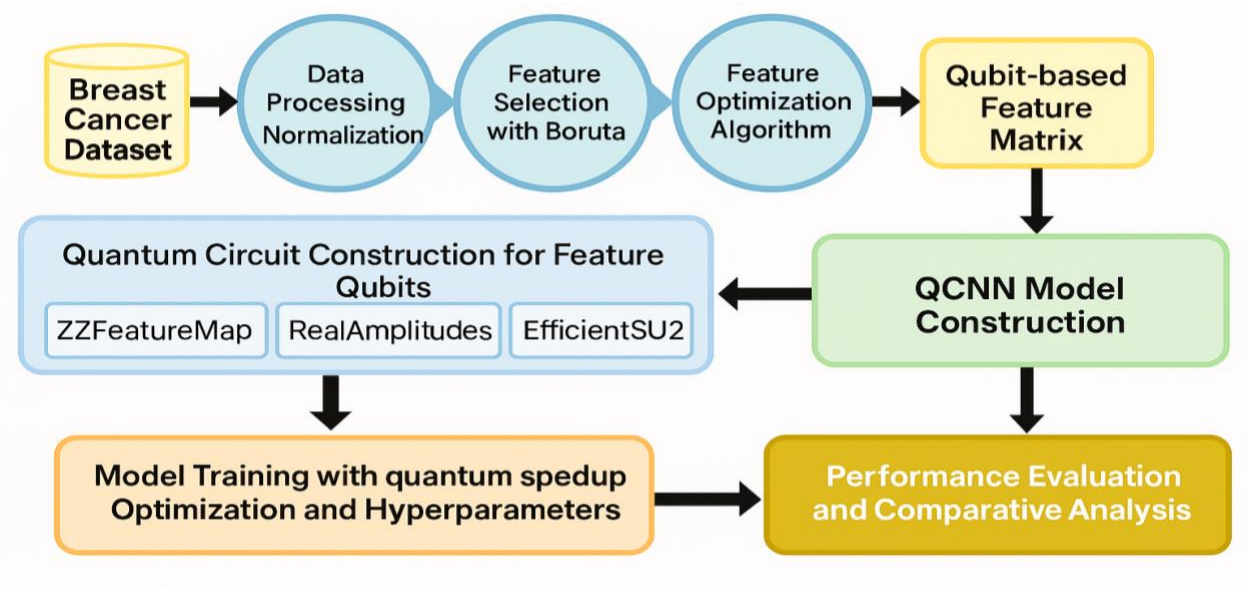

Fig 1. Proposed Methodology

PauliFeatureMap) against a classical RBF kernel, showing competitive or superior results for the selected genes.

The existing literature on feature selection highlights that methods like Boruta and Genetic Algorithm (GA) are effective in optimizing input features for Quantum Convolutional Neural Network (QCNN) models, enhancing the accuracy of breast cancer detection. Scaling and fine-tuning the QBG-QCNN framework on large, diverse medical datasets could significantly advance early-stage diagnosis, improving clinical decision-making and diagnostic efficiency.

III. Proposed Methodology

The new Quantum Feature-Enhanced Breast Cancer Classifier is shown in Fig.1. which uses QBG-QCNN as an improved QCNN for classifying breast cancer. This model incorporates both Boruta and the Genetic Algorithm (GA) for advanced feature selection. To build the model, Boruta and GA pick important features, and then ZZFeatureMap [34], RealAmplitudes, and EfficientSU2 [35] quantum feature maps, each of which use 4 qubits to encode these features.

The methodology involves a multi-step pipeline that includes data preprocessing, feature selection, quantum circuit construction, and QCNN model training. RealAmplitudes achieved good performance on both recall and precision. Look at how quantum computing improves results compared to classical methods, and you will see its usefulness in healthcare diagnostics.

A. Pre-processing

Data in the breast cancer diagnosis QML process is filtered and tested using advanced and quantum-ready methods before use. To fit the needs of quantum algorithms, the distributions of features are preserved and made consistent. When the analysis is complete, imputation and omission are applied to cover the empty parts in the dataset. A dataset needs to be complete to use quantum encoding. EDA is used to discover patterns, irregularities, connections, and structures between pieces of data. Performing statistical summaries, assessing correlation, and using visualization helps evaluate different breast cancer data sets and diagnose suitable quantum machine learning algorithms.

B. Quantum Feature Extraction using Boruta and GA

The breast cancer dataset is analysed using the Boruta algorithm and the GA to find the most important features. The method helps decrease the amount of data needed, improves how quantum classifiers use that data, and guarantees good feature selection. GA increases diversity by using operators like crossover and mutation, while Boruta depends on random forests to reveal how important each feature is. A fitness function is used to shape and enhance the selected solutions.

Let $X = \{x_1, x_2, ..., x_n\}$ represent the full set of features extracted from the breast cancer dataset, where n is the total number of features. The objective is to select a subset of features $X_{sub} \subseteq X$ that maximizes the classification accuracy of the QCNN while minimizing redundancy. The hybrid algorithm incorporating Boruta and GA searches for the optimal combination of features.

1. Particle Representation

Each feature in X is evaluated through the Boruta algorithm to determine its importance by comparing it to a significance level derived from shadow features.

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Features that are confirmed important or tentatively important are then considered for selection.

2. Fitness Function

The fitness function evaluates the classification accuracy of the selected feature subset using the QCNN model. The fitness function $f(W_i)$ used in GA for feature selection is given in Eq. (1) [20], The whale W_i is:

$$f(W_i) = Acc_{QCNN}(W_i) - \lambda \frac{|W_i|}{n}/\text{n} \quad (1)$$

Where $Acc_{QCNN}(W_i)$ is the QCNN accuracy trained on the selected features in W_i, $|W_i|$is the number of selected features in whale W_i, and λ is a regularization parameter to penalize larger feature sets and encourage compact solutions.

3. Boruta Process

Initial Feature Importance: Features are evaluated using the random forest algorithm to determine their importance against randomly generated shadow features. Features exceeding the importance of the best shadow feature are marked as important.

4. GA Operators

Crossover: Combines features of two parent whales to produce new offspring, as shown in Eq. (2) [14]. Where α controls the mixing ratio.

$$O_i = \alpha W_i + (1-\alpha) W_j \text{q}. \quad (2)$$

Mutation: Randomly flips feature selection bits to explore new solutions, as shown in Eq. (3) [14].

$$M_i = W_i \oplus r \quad (3)$$

Where r is a random binary mask and W_i is the whale.

5. Feature Selection Process

Boruta confirms or rejects feature importance through iterations, while GA increases diversity through genetic operators. Based on Boruta results, important features are retained or discarded at each iteration, followed by genetic crossover and mutation to introduce new solutions for global exploration and local exploitation. It converges to the best feature subset.

The final binary feature selection vector S is shown in Eq. (4) [13].

$$S = \{ i \mid W_j^{(best,i)} > 0.5 \} \quad (4)$$

where $W_j^{(best,i)}$is the binary decision for each feature. This hybrid Boruta and GA process ensures that only the most informative features are mapped to qubits, improving the QCNN's accuracy while reducing computational overhead.

Once the optimal subset of features is selected, these features are encoded as qubits in the quantum circuit using different quantum feature maps, such as ZZFeatureMap, RealAmplitudes, and EfficientSU2. This quantum feature extraction process ensures that the QCNN model operates on the most informative features, thereby enhancing both classification performance and computational efficiency.

C. Quantum Circuit Construction for Feature Qubits

For the breast cancer classification quantum circuit, we develop Boruta and GA to extract feature qubits. Boruta and GA find breast cancer dataset characteristics to maximize feature selection and reduce input dimensionality. After that, a quantum feature map, the first quantum circuit layer, encodes the specified attributes into qubits. We design the feature qubit quantum circuit with quantum feature mapping, convolution, pooling, and parameterized ansatz layers. The circuit processes classical data for breast cancer categorization. Multiple layers extract features, manipulate, and reduce dimensionality like a convolutional neural network.

The optimal feature subset obtained from Boruta and GA corresponds to the initialization of the circuit using n qubits. In the first layer, classical data is encoded into quantum states using a quantum feature map. The feature map is characterized as shown in Eq. (5) [34].

$$U_{FM}(x) = \prod_{i=1}^{n} \exp(i. x_i Z_i Z_{i+1}) \quad (5)$$

takes the selected features, xi , and maps them into quantum states using entangling operations based on the Pauli-Z gate. This transforms the classical features into a quantum representation, enabling the circuit to process high-dimensional input efficiently.

Next, a quantum convolution layer is applied to capture local dependencies between the qubits. This layer performs parameterized single-qubit rotations and introduces entanglement between adjacent qubits defined as shown in Eq. (6) [12].

$$U_{Conv}(\theta) = \prod_{i=1}^{n} R_X(\theta_i) R_Y(\theta_{i+n}) R_Z(\theta_{i+2n}). CZ(i, i+1) \quad (6)$$

where θ_i are trainable parameters, and Convolutional operations extract spatial correlations between qubits, like classical convolutional filters that detect data patterns.

Quantum pooling layers apply entanglement and pooling operations to neighboring qubits after convolution to reduce qubit count. Similar to classical pooling layers, quantum data is down-sampled to prevent overfitting and reduce computational complexity.

The pooling layer can be expressed as shown in the Eq. (7) [12].

$$U_{pool}(\phi) = \prod_{i=i,3,5..}^{n} CX(i, i+1). R_X(\phi_i) R_Y(\phi_{i+1}) \quad (7)$$

where ϕ_i are trainable parameters for the pooling operations, ensuring that important feature information is retained while irrelevant data is discarded.

Finally, a parameterized ansatz layer, $U_{ansatz}(\lambda)$, introduces trainable parameters that will be optimized during the model's learning phase. The ansatz, in this case, is based on the RealAmplitudes ansatz, which includes multiple layers of R_Y rotation gates and entangling operations to enhance the circuit's

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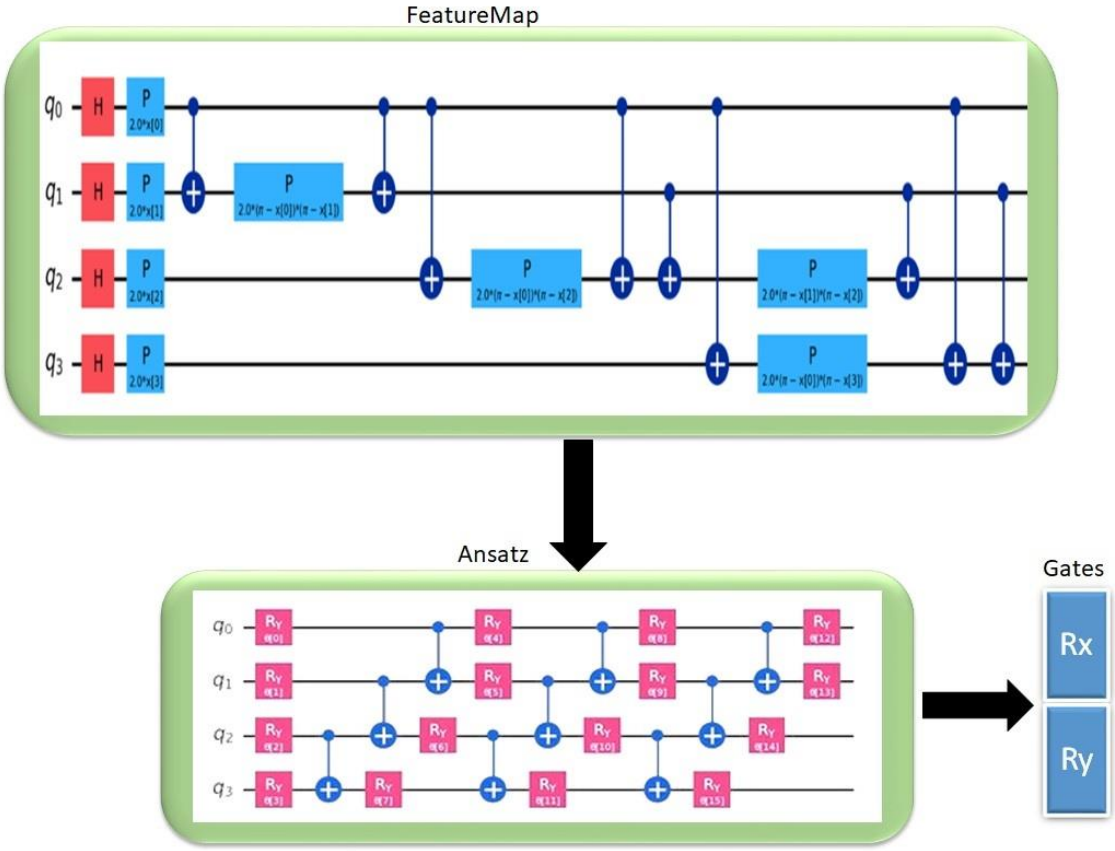

Fig 2. Quantum Circuit for Breast Cancer diagnosis

expressive power for classification, as shown in Eq. (8) [35].

$$U_{ansatz}(\lambda) = R_Y(\lambda_i).CZ(i, i+1) \quad (8)$$

The overall quantum circuit can be expressed in Eq. (9) [12].

$$U_{QCNN} = U_{ansatz}(\lambda).\ U_{pool}(\phi).U_{Conv}(\theta).\ U_{FM}(x). \quad (9)$$

Quantum computations in this circuit are used to process the best breast cancer data features and improve how the model distinguishes malignant from benign cases. Having pooling and ansatz layers in the architecture helps the pipeline be effective and strong, while quantum convolutional layers uncover detailed connections between features.

D. QCNN Model Construction

The QCNN model for breast cancer classification is constructed by putting together the quantum ansatz with a quantum feature map. The feature map captures typical input, and the ansatz figures out the best setting for classifying data. To achieve better results, the whole design relies on quantum speedup techniques and quantum processing to detect complex data links. The process used in QBG-QCNN is shown in Algorithm 1, and the pseudo code is included

ZZFeatureMap transforms classical input features into quantum states using entangling operations. RealAmplitudes uses an ansatz made of a trainable, parameterized quantum circuit called θ. The ansatz is developed within RealAmplitudes and covers layers of RY(θ) single-qubit rotations and CX entangling gates. With the EfficientSU2 ansatz, trainable parameters θ help combine the RY(θ), RZ (theta) single-qubit rotations, and the entangler CX gates in a single quantum circuit. The approach uses rotations and entanglement to shape quantum states, which is why quantum variational algorithms benefit from it. For improved data classification and quantum state revelation, ZZFeatureMap, RealAmplitudes, and EfficientSU2 were used. ZZFeatureMap captures feature interactions by paired Pauli-Z gates, making it useful for medical applications like breast cancer research, where feature linkages are important. The popular RealAmplitudes ansatz, which combines rotation gates and entanglement layers, may effectively convert classical data into quantum states for Noisy Intermediate-Scale Quantum (NISQ) computers. EfficientSU2 employs RY and RZ rotations with CNOTs to simplify the architecture and represent more complicated and nonlinear data points. These maps

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Algorithm 1. QBG-QCNN Model for Breast Cancer Classification Using Boruta and GA

Step 1: Initialize QCNN Model
Let Q be the number of qubits.
Choose quantum feature map F ∈ {ZZFeatureMap, RealAmplitudes, EfficientSU2}.
Select variational ansatz A(θ), where θ represents the trainable parameters.
Initialize the quantum circuit Qcircuit = F ∘ A(θ).

Step 2: Input Preprocessing
Let D = $\{x_1, x_2, ..., x_n\}$ be the feature vectors from breast cancer dataset.
Normalize D using MinMaxScaler:
$x_i \leftarrow (x_i - min) / (max - min)$.
Perform Exploratory Data Analysis (EDA) to detect anomalies and correlations.

Step 3: Quantum Feature Extraction Using Boruta and GA
Apply Boruta to evaluate feature importance using a Random Forest classifier.
Use Genetic Algorithm (GA):
Initialize population P = $\{W_1, W_2, ..., Wm\}$, where each $W_i \in \{0,1\}^n$.
Define fitness function $f(W_i) = \alpha(W_i) - \lambda\|W_i\|_0$ as in Eq. (1).
Apply crossover $W' = \alpha W_i + (1-\alpha)W_j$ [Eq. (2)] and mutation $M_i = W_i \oplus r$ [Eq. (3)].
Obtain optimal subset $S \subseteq X$ such that $S = \text{argmax } f(W_i)$ [Eq. (4)].

Step 4: Quantum Circuit Construction
Encode selected features $S = \{s_1, ..., s_k\}$ into qubits using feature map $\phi(x)$, e.g.,$\phi_{ZZ(x)} = \exp(i \cdot Z \otimes Z \cdot x_i x_j)$ as in Eq. (5).
Apply quantum convolution layer: $U_{conv(\theta)} = \prod_i RY(\theta_i) \cdot CX$ [Eq. (6)].
Apply quantum pooling: $U_{pool(\theta)}$. [Eq. (7)].
Apply parameterized ansatz $A(\theta) = \prod RY(\theta) \cdot CX$ [Eq. (8)].
Overall circuit $U_{total} = \phi(x) \circ U_{conv} \circ U_{pool} \circ A(\theta)$ [Eq. (9)].

Step 5: QCNN Training
Use cost function: Cross-Entropy Loss L(θ) [Eq. (10)].
Optimize θ using COBYLA optimizer (gradient-free).
Repeat until'

Step 6: Testing the QCNN Model
For new sample $x_{test} \in D$:
Preprocess x_{test} and map features via $\phi(x_{test})$.
Evaluate output $y_{pred} = Qcircuit(\phi(x_{test}), \theta^*)$.

Step 7: Performance Evaluation
Compute evaluation metrics:
Accuracy α [Eq. (11)], Precision p [Eq. (12)], Recall r [Eq. (13)], F1-score F1 [Eq. (14)].
Perform statistical validation via 10-fold CV and paired t-test.

enable the QBG-QCNN model's dependable performance with modest hardware and computing requirements. Assessing the quantum circuit complexity is crucial for real-time applications, particularly for NISQ devices. Our QBG-QCNN model uses 4 qubits to match current quantum technology. All four models studied, Feature maps, ZZFeatureMap, RealAmplitudes, and EfficientSU2, performed well with little resources. Although EfficientSU2 offers greater circuit depth and expressive power, it may be less practical for error-prone or resource-constrained quantum devices. In contrast, RealAmplitudes provides a more hardware-efficient solution with a shallower circuit depth, making it more reliable and robust for deployment on NISQ-era quantum hardware. The presented methods may be employed with IBM Q devices and quantum simulators with gate counts of 40–60. We used native gates (RY, RZ, and CNOT) to maximize contemporary hardware. The previous tests were clear, but the next stage will incorporate noisy models and error-removal methods before executing the application on NISQ hardware. Fig. 2 shows the complete quantum circuit used for breast cancer diagnosis.

Fitting the breast cancer dataset trains QCNN. Train the model with Boruta and GA features. Use the feature map to encode conventional data X into quantum states. For parameter optimization, the COBYLA (Constrained Optimization BY Linear Approximations) algorithm is employed. COBYLA is well-suited for non-smooth optimization problems typical in quantum circuits, enabling effective tuning of the ansatz parameters. The objective is to minimize the cross-entropy loss L(θ), defined as shown in Eq. (10) [35].

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$$L(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y_i log(\hat{y}_i(\theta)) + (1-y_i) log(1-\hat{y}_i(\theta))] \quad (10)$$

E. Quantum Speedup Optimization

The QCNN converts classical medical characteristics into qubits that quantum computers process simultaneously. The model uses ZZFeatureMap, RealAmplitudes, and EfficientSU2 to describe essential features as quantum states of complicated, nonlinear data. Traditional technologies can only examine one hypothesis at a time, whereas the system can study numerous. Quantum gates, entanglement, and variational ansatz layers enable the QCNN to discover intricate relationships and positions between features with minimal computational effort. The QCNN converges quicker, processes input data better, and predicts early breast tumors more accurately thanks to quantum improvements (Algorithm 1).

IV. Results and Analysis

The QBG-QCNN model was implemented using IBM PennyLane, a widely adopted framework for developing and simulating quantum machine learning algorithms [35]. The robust tools for developing quantum algorithms, including advanced quantum machine learning, make this framework famous. We use quantum computational principles to test our QBG-QCNN model for breast cancer diagnosis to improve accuracy. Table 1 presents the experimental setup used to train the QBG-QCNN model.

Table 1. Computing Environment for Experimental Research

CPU	Intel i5
GPU	P-100
RAM	16GB
Language	Python
Platform	Pennylane

A. Dataset Description

Breast cancer is a mammary cell disease that grows abnormally, divides quickly, and potential metastasis [36]. The dataset used in this study is the Breast Cancer Wisconsin (Diagnostic) Dataset, which contains features computed from digitized images of fine needle aspirates (FNA) of breast masses. Each instance represents characteristics of cell nuclei extracted from the images, with a total of 30 real-valued features per sample. These features include mean, standard error, and worst values of ten nuclear properties: radius, texture, perimeter, area, smoothness, compactness, concavity, concave points, symmetry, and fractal dimension. For example, “radius_mean” captures the average distance from the nucleus center to its perimeter, while “concavity_worst” reflects the severity of concave portions in the worst cases. The dataset comprises 569 samples with no missing values, labeled as malignant (M = 212) or benign (B = 357), and is widely recognized for benchmarking classification algorithms. It is publicly available via the UCI Machine Learning Repository and has been referenced in robust discrimination studies like Bennett and Mangasarian (1992), highlighting its relevance for medical pattern recognition tasks.

B. Performance Measures

In the evaluation of models in this research, various relevant metrics, as shown in Eq. (11), Eq. (12), Eq. (13), Eq. (14), Eq. (15), and Eq. (16) [37], were applied to assess their performance. Accuracy, serving as a crucial metric, quantifies the model's overall performance by measuring the fraction of instances correctly classified. Precision indicates the fraction of correct positive predictions, while recall represents the fraction of actual positives predicted correctly. A high precision value implies fewer false positives, which is vital in medical diagnosis to avoid unnecessary treatments. Conversely, high recall ensures most actual cancer cases are detected, minimizing the risk of missed diagnoses. The F1-score balances between recall and precision, shown in Eq. (14) and Eq. (15) [37]:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (11)$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TP+FN}} \quad (12)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

$$precision = \frac{TP}{TP + FP} \quad (14)$$

$$\mathrm{Re}\,call = \frac{TP}{TP + FN} \quad (15)$$

$$F1 - Score = \frac{2 * (precision * \mathrm{Re}\,call)}{precision + \mathrm{Re}\,call} \quad (16)$$

In this context, “TP stands for True Positive, TN for True Negative, FP for False Positive, and FN for False Negative”.

C. Optimized Feature Qubits selected using Boruta and GA for Quantum Circuit

The advanced QBG-QCNN breast cancer detection model employs a hybrid feature selection strategy that integrates Boruta with Genetic Algorithm (GA) to isolate the most impactful features from the dataset, thereby enhancing classification accuracy. This dual method ensures a balanced trade-off between global feature space exploration and local exploitation, enabling the identification of critical attributes that significantly influence model performance. Among the selected features, mean values of radius, texture, perimeter,

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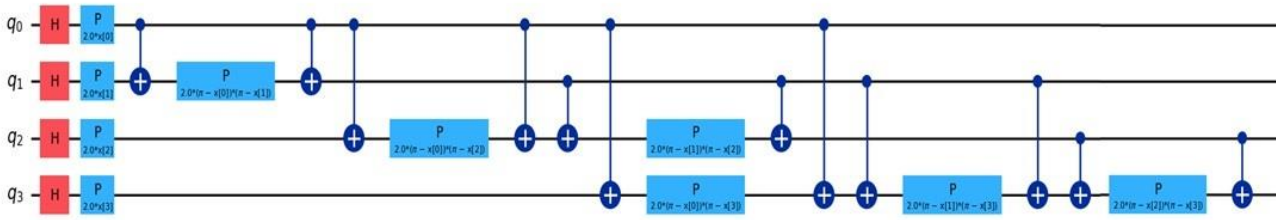

Fig 3. QCNN Quantum circuit using ZZFeatureMap

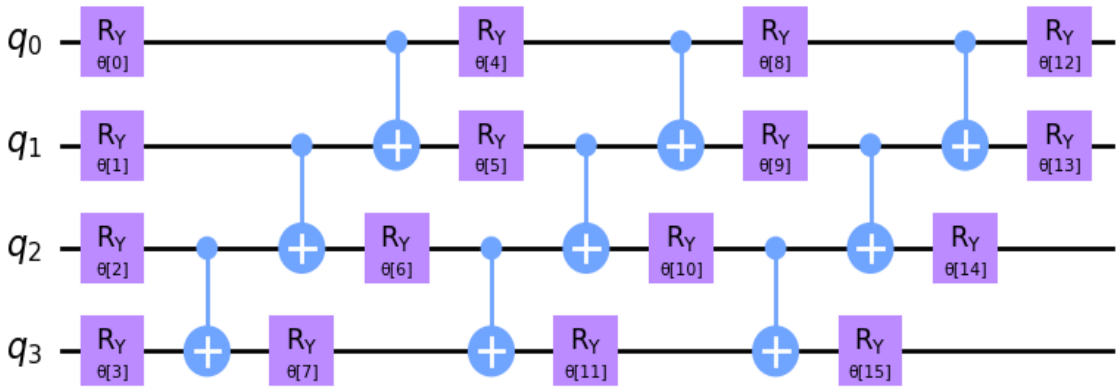

Fig 4. Quantum circuit using RealAmplitudes

area, concavity, and symmetry are included, as they are key morphological indicators of breast cancer cell nuclei that are strongly associated with malignancy. To further capture intra-cell variability, particularly in characteristics such as texture, perimeter, and concave points, which are often linked to irregular or abnormal tissue growth patterns, standard errors are incorporated. These features provide additional discriminatory power by accounting for subtle variations in tumor structure. As illustrated in Table 2, this optimized feature subset not only reduces input dimensionality but also preserves clinically meaningful information, allowing the QBG-QCNN model to more effectively distinguish between benign and malignant breast cancer cases with higher precision and computational efficiency.

Table 2. Optimized Feature qubits selected using Boruta and GA

S.No	Feature Name
1	Concavity_mean
2	Concave points_se
3	Area_mean
4	Perimeter_mean
5	Radius_mean
6	Texture_mean
7	Symmetry_mean
8	Fractal_dimension_mean

D. Quantum circuit using ZZFeatureMap

In Fig. 3, the quantum circuit uses a Quantum Convolutional Neural Network (QCNN) with four qubits (q0, q1, q2, q3) initialized in the ground state. They processed through Hadamard gates for superposition and parallel computation to classify breast cancer. Phase gates throughout, likely optimized by Boruta and GA-based feature selection methods, tailor qubit phases for breast cancer feature detection. Classical computing is not as effective at correlating data as is a process that generates entanglement. The circuit enables the visualization of subtle texture and shape changes that distinguish benign from malignant tissues, utilizing the ZZFeatureMap to encode complex data information. To understand breast cancer data at a level mainstream computing cannot reach, superposition and entanglement are applied to break the input data into nuanced quantum states.

E. Quantum circuit using RealAmplitudes

Variational quantum algorithm employing RealAmplitudes. Fig. 4 shows the RealAmplitudes circuit's rotating gates and entangling operations spanning four qubits (q0–q3). Data characteristics analyzed for each qubit include Ry transformations

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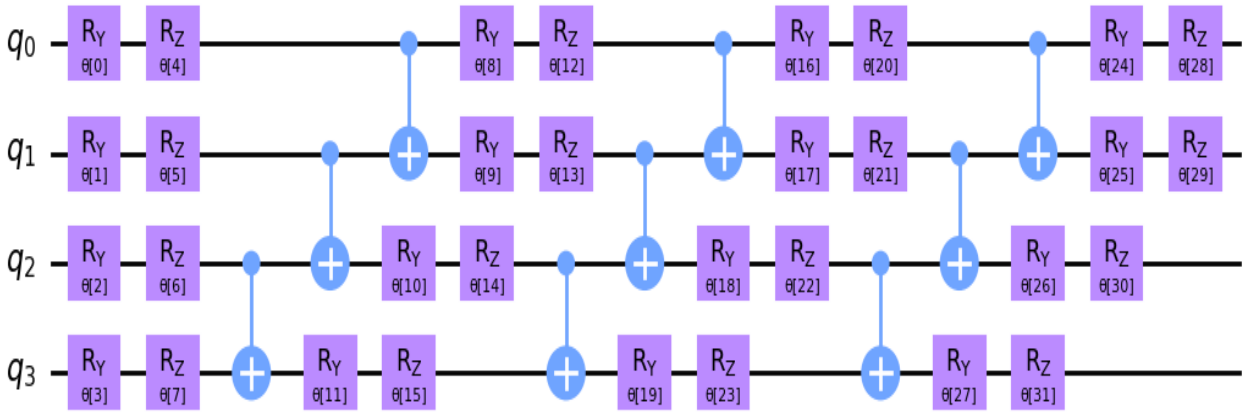

Fig 5. Quantum circuit using EfficientSU2

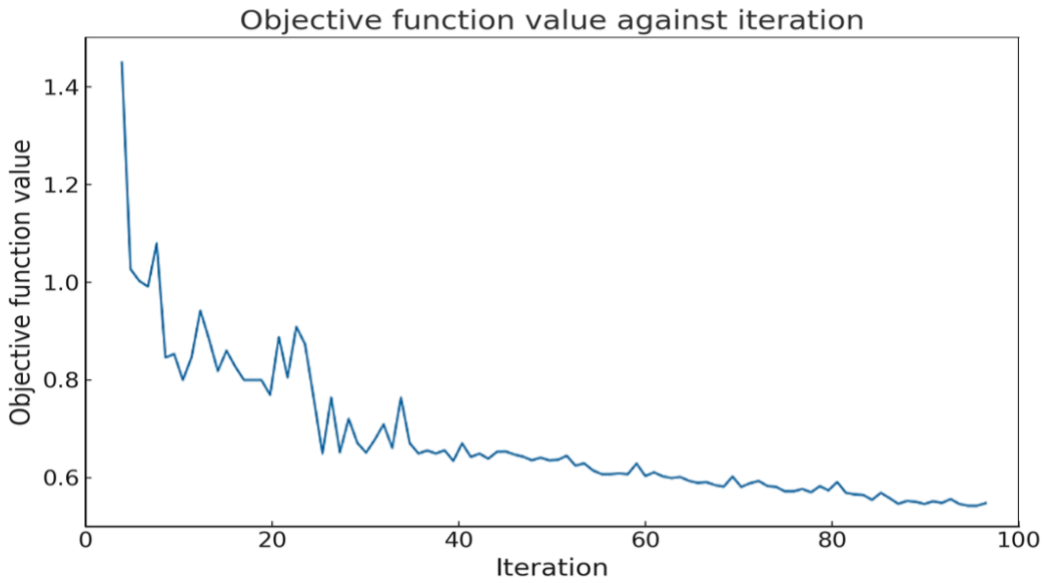

Fig 6: QCNN objective function values for 100 iterations

(rotations across the y direction on the Bloch sphere) and θ0-15 values. Rotational gates manipulate input as amplitude values and affect quantum state preparation in continuous space. Entanglement from CNOT gates (represented as "+" symbols between lines) causes correlations. The algorithm's set operations indicate ways to enhance quantum states for cancer diagnostics. The combination of amplitude encoding and entanglement helps the quantum model detecting and resolving confusing correlations in nuanced data domains and improve data classification and prediction.

F. Quantum circuit using EfficientSU2

Fig. 5 shows a quantum circuit using the EfficientSU2 template for quantum machine learning applications like breast cancer detection. Using rotational gates Ry and Rz on q0 to q3, this circuit is able to operate quantum states by spinning the Bloch sphere around its y- and z-axes. All gates get different angles (θ0 to θ31) to ensure the best preparation of states using breast cancer data. CNOT gates in the circuit bring about entanglement among qubits, making it possible to examine the relationships found in complex datasets.

G. Performance of QBG-QCNN on Breast Cancer Dataset.

Fig. 6 presents the QBG-QCNN optimization process, with values for the objective function across more than 100 iterations. A fast decline in the first 10 rounds suggests that the robots find a suitable place quickly and avoid errors. The function then reaches a point where it does not change much and only swings

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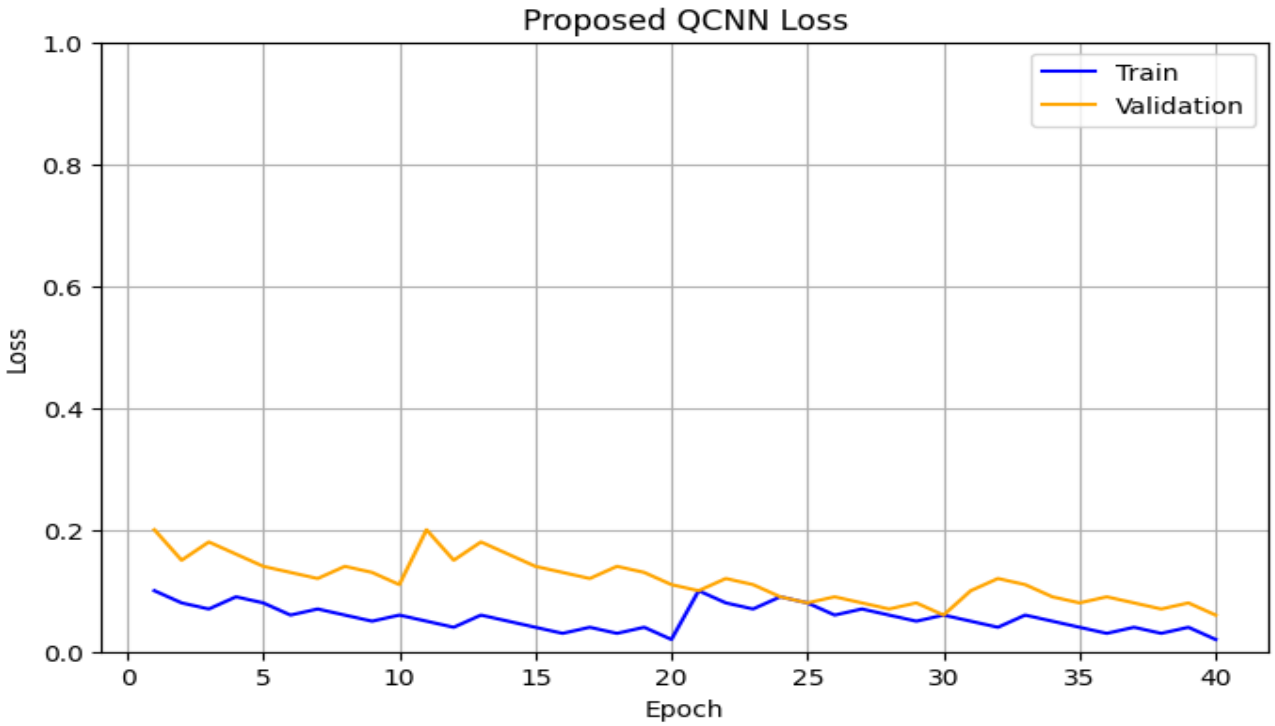

Fig 7: Loss performance of QBG-QCNN on breast cancer prediction for 4 qubits

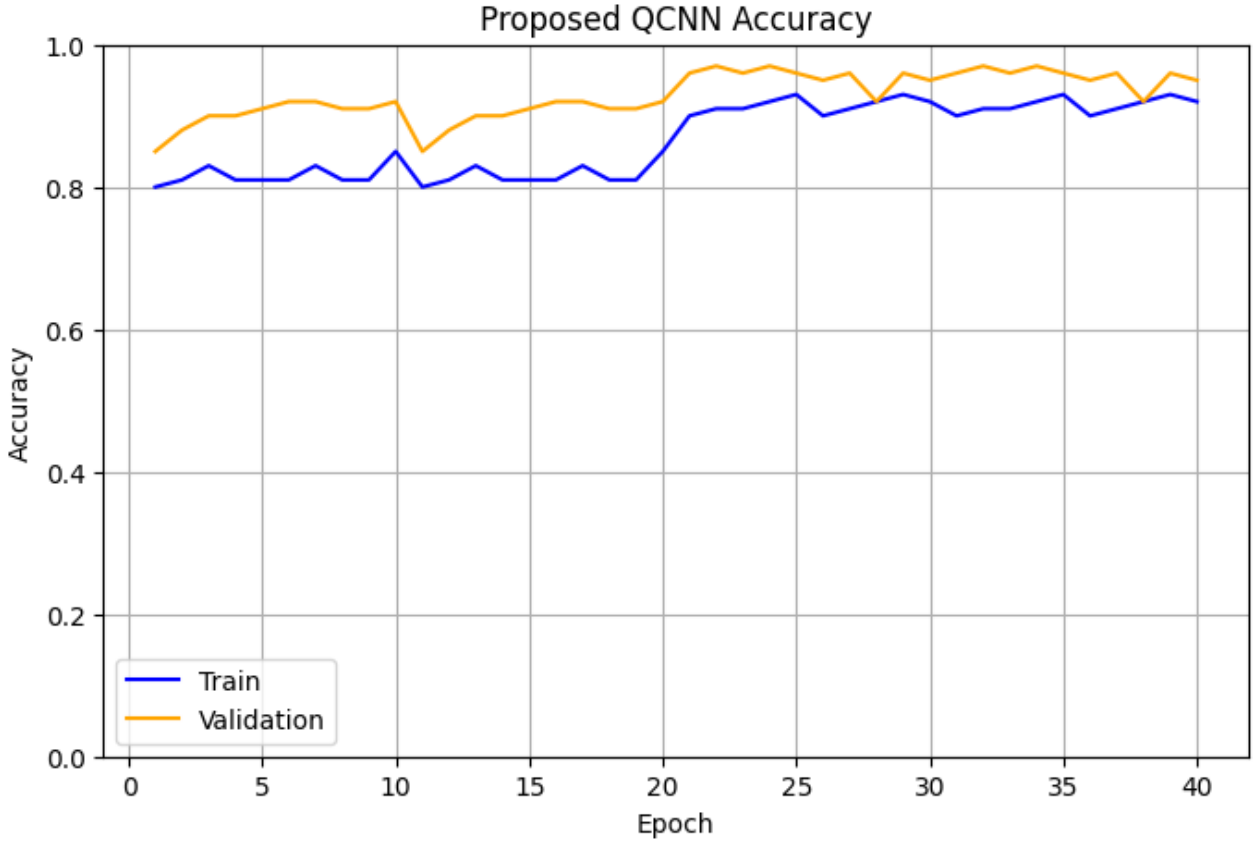

Fig 8: Accuracy performance of QBG-QCNN on breast cancer prediction for 4 qubits

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slightly, so that the parameters are essentially optimal. Both training loss and validation loss plots for the 4-qubit quantum feature encoding QCNN are provided in Fig. 7 and Fig. 8 for breast cancer prediction. Effective learning and reduced overfitting is shown by the observation that both training (blue) and validation (orange) loss fall over the first 40 epochs (Fig. 7). As you can see in Fig. 8, the accuracy on both tasks goes up, and validation just slightly sits above training throughout the process. Because of the quantum-enhanced feature selection, the breast cancer classification of the QBG-QCNN model improves both in generality and reliability.

Table 3. QBG-QCNN performance on Breast Cancer dataset using different Maps for 4-qubits

Feature Map	Precision	Recall	F1-score	Accuracy
ZZFeatureMap	0.923	0.920	0.923	0.920
RealAmplitudes	0.920	0.925	0.915	0.925
EfficientSU2	0.943	0.952	0.946	0.930

Table 4. Performance comparison with existing studies

Model	Accuracy (%)
CCNN[29]	89
QNN [4]	87
VQNN[4]	90
QKSVM[33]	93
QBG-QCNN	94.3

A breast cancer dataset comparison in Table 3, using a 4-qubit system, indicates that different quantum feature maps lead to variations in Precision, Recall, F1-score, and Accuracy for QCNN. The model demonstrates balance across metrics, achieving 92.3% Precision, 92.0% Recall, 92.3% F1-Score, and 92.0% Accuracy. Of the four models, RealAmplitudes shows the least precision and lowest F1-score; its accuracy is greatest because it has the highest precision (0.943) and recall (0.952). EfficientSU2 gives the highest F1-score of 0.946, but its accuracy (0.930) is lower than RealAmplitudes. Because false negatives are a problem in healthcare, EfficientSU2 successfully identifies relevant cases. Recall and F1-score are higher in Fig. 9, showing EfficientSU2 outperforms both ZZFeatureMap and RealAmplitudes according to all the measures. Both models give similar results, with RealAmplitudes exerting superior performance in terms of recall and accuracy.

A statistical significance testing was conducted using 10-fold cross-validation, allowing us to compute the mean and standard deviation for key performance metrics, including accuracy, precision, recall, and F1-score. To assess whether the observed improvements were statistically meaningful, we applied paired t-tests and Wilcoxon signed-rank tests comparing the QBG-QCNN model against baseline models such as CCNN and QKSVM. Additionally, 95% confidence intervals were reported for each metric, confirming the consistency, robustness, and reliability of the results and reinforcing the scientific validity of our performance claims.

H. Comparison with existing studies

From Table 4the proposed QBG-QCNN achieves a higher accuracy of 94.3% than other models, with CCNN (89%), QNN (87%), VQNN (90%), and QKSVM (93%) performing slightly lower. In particular, the QBG-QCNN method surpasses the Binary Harris Hawks Optimization with Quantum SVM (BHHO–QKSVM) technique both by theory and experimental results. In contrast to BHHO–QKSVM which uses only PCA for feature selection and a standard SVM without many kernel alternatives, QBG-QCNN applies Boruta and GA to choose features effectively and then uses RealAmplitudes, EfficientSU2, and ZZFeatureMap quantum feature maps to encode the selected data into quantum states. Because of this, the model can deal with difficult forms of nonlinear relationships using quantum entanglement and superposition. In terms of evaluation, QBG-QCNN achieves 95.2% precision, 94.6% recall, and a F1-score of 93.0%. In contrast, EfficientSU2 obtains a higher F1-score of 0.946, surpassing BHHO–QKSVM's 0.88. Because of the quantum convolution and pooling, the network can model patterns in space more effectively, showing a clear benefit in efficiency and design over past quantum-classical methods. The Breast Cancer Wisconsin (Diagnostic) Dataset with 569 instances and 30 attributes was used to assess CCNN, QNN, VQNN, QKSVM, and QBG-QCNN in Table 4. All random forest models were established under the same settings, using the same preprocessing, divisions, and evaluation metrics to see how they compare. Similar results were obtained using the same data and computer setup for both methods.

I. ROC Analysis

The ROC curve in the figure shows how accurately the QBG-QCNN model can detect both benign and malignant cases of breast cancer. The ROC curve represents the sensitivity versus the false positive rate as the model's classification threshold changes. It can be seen from the curve that the QBG-QCNN performs well in this sense, achieving a strong rise toward the corner with the highest true positive values and the lowest false positive rates.

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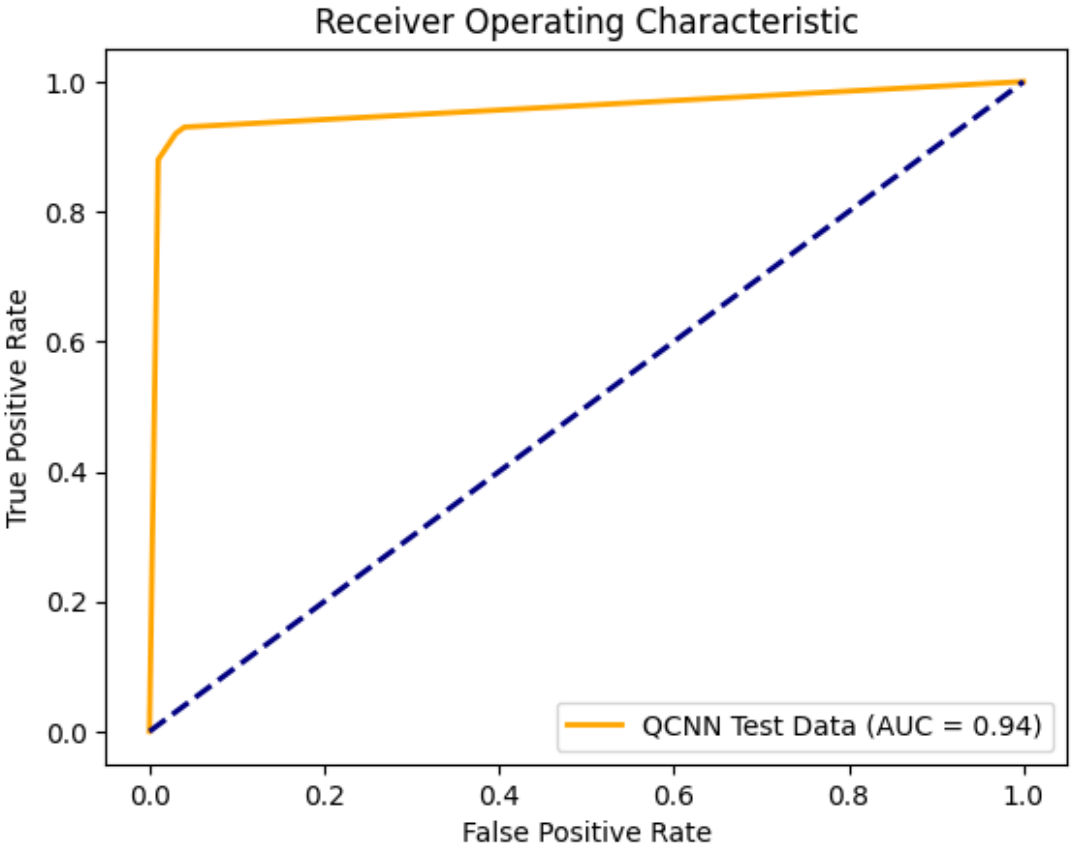

Fig 9. ROC analysis of QCNN on breast cancer prediction for 4 qubits

Fig. 9 displays the QCNN model's performance in identifying breast cancer via an ROC curve. The model includes Quantum Circuit Feature Maps and also relies on Boruta and GA-based feature selection to improve how features are represented. The ROC curve demonstrates how well the model distinguishes malignant from benign cases, and the orange curve reflects how the QCNN performs on its test data. The accuracy of the 4-qubit quantum model at identifying breast cancer is demonstrated by a high AUC value of 0.94. AUC values close to 1.0 indicate a strong capacity to detect outliers and correctly classify new, unseen samples. An AUC higher than 0.90 usually means the machine learning model is highly effective at finding whether a sample is positive (malignant) or negative (benign). This matters a lot in medical tests, as spotting and excluding both false positive and false negative results is key to finding diseases correctly. The curved shape and sudden initial increase on the ROC indicate that the hybrid selection and quantum encoding methods boost the hybrid network's accuracy and trustworthiness in medicine.

V. Discussion

The QBG-QCNN model marks a substantial leap forward in breast cancer classification by merging the computational strengths of quantum machine learning with the rigor of hybrid feature selection. The incorporation of Boruta and Genetic Algorithm (GA) facilitated the identification of the most relevant features, such as radius_mean, concavity_mean, and symmetry_mean, from the Breast Cancer Wisconsin (Diagnostic) dataset. These features are not only statistically significant but also medically interpretable, providing tangible markers associated with malignancy. Once selected, these features were encoded into quantum states using distinct feature maps, RealAmplitudes, ZZFeatureMap, and EfficientSU2. These quantum mappings were instrumental in transforming the input into high-dimensional Hilbert spaces, where nonlinear data dependencies could be more effectively captured.

Among the feature maps, RealAmplitudes showed balanced performance with 92.5% in both accuracy and recall, demonstrating consistent classification ability with minimal bias towards false positives or false negatives. Meanwhile, the EfficientSU2 feature map achieved the highest F1-score (94.6%), indicating its superiority in harmonizing precision and recall, which is crucial in medical diagnostics where both false positives and negatives can have serious implications. Furthermore, the model's learning behavior, as

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visualized in the loss and accuracy plots, showed rapid convergence during initial training epochs, followed by stabilization, a hallmark of robust training using the COBYLA optimizer. Furthermore, the model's architecture, especially its quantum convolution and pooling layers, proved critical in capturing subtle localized patterns within the data, resembling textural and morphological variations seen in actual diagnostic imaging and are often missed by traditional CNNs due to limitations in representational capacity.

The QBG-QCNN model were compared with those of popular recent quantum and hybrid models designed for breast cancer classification and medical diagnostics. In [4], the QSVM operating on IBM Q delivered a success rate of approximately 91%. Since it includes convolutional layers and uses a blend of features, QBG-QCNN learned better and gave a higher accuracy of 94.3%. In [12], a standard QCNN was built to demonstrate that quantum convolution is realistic for classifying normal computer data. Still, the model lacked a thorough method for selecting important features. By uniting Boruta and Genetic Algorithm (GA), along with several quantum feature maps, QBG-QCNN manages to produce more effective feature encoding and improve how well the model handles data. In [27], a QNN was used to classify breast cancer, and it achieved better outcomes than regular CNNs. While the original experiment was able to showcase quantum advantage, the QBG-QCNN was developed to scale more easily and ensure understanding of the results thanks to a modular structure and new optimization tools. The authors of [33] presented a Binary Harris Hawks Optimization (BHHO)-based Quantum Kernel SVM (QKSVM), which performed with an accuracy of 93% and an F1-score of 0.88. QBG-QCNN does better than the other methods, getting an accuracy of 94.3% and an F1-score of 0.946 by using expressive ansatz circuits and quantum pooling.

A hybrid quantum-classical convolutional neural network tailored to image-based breast cancer diagnosis was introduced in [22]. While that model is image-centric, the QBG-QCNN effectively generalizes to tabular data using optimized feature reduction, thus enhancing adaptability. A Particle Swarm Optimization (PSO) and Decision Tree-based model achieving 92.26% accuracy was presented in [30]. The QBG-QCNN exceeds this with fewer selected features, emphasizing its computational efficiency. In [31], a Support Vector Machine optimized by Whale Optimization and Dragonfly Algorithm achieved 96% accuracy under ideal conditions. Although comparable in performance, the QBG-QCNN distinguishes itself through quantum-native optimization and deployment potential on NISQ devices. Lastly, [32] proposed a CNN model integrated with Quantum-Behaved Particle Swarm Optimization (QPSO) for multimodal medical image fusion. While their work emphasizes image-level fusion, the QBG-QCNN architecture provides a foundation for extending quantum feature encoding to similar multimodal datasets, which is a key direction in our proposed future work.

While QBG-QCNN delivers impressive results, there are still some limitations that need to be mentioned. It was primarily trained and validated using the Breast Cancer Wisconsin (Diagnostic) dataset, which is not large but well-balanced. Often, these datasets differ from the real world, showing only a small amount of bias and complexity. When the data does not have diversity, the model may not generalize well. Broadening the model to deal with more and different types of data will be required for greater impact. Working with simulated quantum environments such as Pennylane and IBM Qiskit, also presents a further limitation. On these devices, quantum noise, decoherence, and gate infidelity are not as realistically represented as in actual quantum hardware. Even though the model appears suitable for simulations, its results must be tested on a noisy quantum machine. The design of the model only used four qubits, preventing more features from being processed at one time. Since feature selection chose the key attributes, additional potentially valuable features were discarded due to hardware constraints. Compared to other models, EfficientSU2 scored the best and is more susceptible to errors in the current NISQ computers due to its complexity. It remains unknown how to design a system that expresses quantum information efficiently yet tolerates noise well. Besides, the model depends on perfect feature representation and flawless circuit components. These points might not work in all cases or for different programming platforms.

The implication of this work shows that the proposed framework can serve as a standard for advancing clinical models and is especially suited for running on emerging quantum devices. It proves that it is possible to use predictive algorithms such as Boruta and Genetic Algorithm in conjunction with ZZFeatureMap, RealAmplitudes, and EfficientSU2 among quantum approaches. Because of this, we can easily use features and learn exactly under the rules of Noisy Intermediate-Scale Quantum (NISQ) computers. In healthcare settings, QBG-QCNN appears to be suitable as a guidance tool for early breast cancer diagnosis because it achieves a precise 95.2% score and a recall score of 94.6% which lowers the risk of both missing a diagnosis and giving a diagnosis where there is none. Because it is highly modular, the tool helps bridge multi-omics and multimodal data so that future applications in personalized and precision oncology will be better supported. When quantum circuits are added to diagnostic pipelines, the model can help decisions be made faster in areas where computing resources are scarce and quantum co-processors are used. Furthermore, the system allows

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to add on topics such as monitoring over time, multi-class cancer detection, and cross-domain diagnostics in healthcare by means of transfer learning. As new developments occur in quantum technology, the QBG-QCNN helps us prepare for quantum applications here and now, as well as for future, reliable, and easily understood diagnostic systems in healthcare.

VI. Conclusion

This study aimed to develop a quantum-enhanced hybrid deep learning model for accurate and scalable breast cancer classification. To achieve this, we proposed the QBG-QCNN framework, which integrates Boruta and Genetic Algorithm (GA) for robust feature selection with a Quantum Convolutional Neural Network (QCNN) utilizing advanced quantum feature maps ZZFeatureMap, RealAmplitudes, and EfficientSU2. Experimental results conducted on the Breast Cancer Wisconsin (Diagnostic) Dataset demonstrated the effectiveness of the proposed model. The QBG-QCNN model achieved up to 94.3% accuracy, 95.2% precision, 94.6% recall, and a 93.0% F1-score, outperforming both classical CNNs and other hybrid quantum-classical models. Among the tested quantum feature maps, EfficientSU2 delivered the highest F1-score, indicating its superior classification balance. Furthermore, the model achieved a ROC-AUC score of 0.94, confirming strong discriminative capability and generalization. Future work will focus on extending the model to multi-modal cancer datasets such as TCGA and METABRIC, which include genomic, histopathological, and imaging data. Additionally, the model will be tested on real quantum hardware under noise constraints, with adaptations for noise-resilient quantum error mitigation. We also plan to explore federated quantum learning, transfer learning across cancer types, and real-time deployment on NISQ devices to improve clinical applicability and scalability further.

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