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A Hybrid Quantum-Classical Model for Breast Cancer Diagnosis with Quanvolutions

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***Abstract*—This paper explores the potential of quantum machine learning for breast cancer detection. We designed a binary classification approach using the BreastMNIST dataset and segmented mass regions derived from the BCDR dataset. A quanvolutional layer is employed as a quantum feature extractor, interfaced with elements of classical neural networks, to enhance the detection of malignant and benign patterns in breast tissue. The hybrid quanvolutional neural network aims to mitigate challenges associated with traditional machine learning models, such as feature sparsity and data imbalance. This architecture employs a simple yet efficient design that integrates the strengths of both quantum computing and classical methods, reducing computational complexity while maintaining performance. Results demonstrate the potential of quanvolutions in diagnostic accuracy, offering a promising framework for integrating quantum computing in medical imaging. This approach provides an optimized solution that balances quantum processing with classical systems for more effective and scalable applications.**

***Index Terms*—quantum machine learning, artificial intelligence, breast cancer, quanvolutional neural networks, medical imaging, quantum computing.**

I. INTRODUCTION

Breast cancer remains one of the most significant health challenges faced by women worldwide. In 2022 alone, 2.3 million women were diagnosed, and the disease accounted for 670,000 deaths globally [1]. It affects women worldwide and can occur at any age after puberty, though its incidence rises significantly in later life. These statistics emphasize the pervasive nature of breast cancer and reinforce its status as a leading cause of mortality among women. Early and accurate detection is critical in improving survival rates, as timely intervention enables more effective treatment and better prognoses. Consequently, advancing diagnostic methods remains a top priority in reducing the global burden of this disease.

Current breast cancer diagnostic techniques, such as mammography, ultrasound, and biopsy, have been instrumental in the detection of the disease in the early stages [2]. Mammography, in particular, is widely regarded as the gold standard for breast cancer screening due to its non-invasive nature and ability to detect abnormalities. In certain circumstances, additional imaging tools such as whole breast ultrasound (WBUS) and magnetic resonance imaging (MRI) are used as a complement. While they provide valuable diagnostic information, they also come with limitations. Both tend to produce higher rates of false positives, and MRI is significantly more expensive than standard mammography, with limited availability in some healthcare settings. Despite their benefits, neither replaces mammography as the primary screening method but instead serves as a supplementary tool in cases requiring further evaluation [3].

Those techniques rely heavily on human interpretation, making diagnostic accuracy susceptible to variability in radiologist expertise. Interpreting screening mammograms is a complex and challenging task. A large-scale study involving 418,041 women and 110 radiologists found that the overall sensitivity of radiologists was 73%, meaning approximately 27% of cancers were either missed or not acted upon. Notably, even among high-volume screen readers—radiologists who interpreted over 5,000 screening mammograms annually—sensitivity remained relatively low. When double reading and consensus discussions were implemented, the overall sensitivity improved to 85% [4]. Although some diagnostic errors are unavoidable in perceptual tasks, persistently high error rates highlight a critical need for improved accuracy in breast cancer detection. To address these errors, various computerized tools have been developed to assist radiologists. In this context, machine learning (ML) techniques can be a foundation for future improvements in early-stage breast cancer screening.

Machine learning has played a pivotal role in advancing medical imaging by improving diagnostic accuracy and reducing human variability in interpretation. These AI-driven approaches help to mitigate false positives, false negatives, and inter-reader variability, making them valuable tools in breast cancer screening and diagnosis [5]. Deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), have demonstrated advancements in image-based diagnosis. However, as medical imaging datasets grow in complexity, developing more efficient and generalizable models remains an ongoing challenge [6]. There are still limitations regarding practical applications and the need for preparation for future paradigms.

Quantum computing is a developing field that offers new possibilities for machine learning by using principles such as **superposition** and **entanglement** to process information differently from classical methods. While still in its early stages, quantum machine learning (QML) has shown potential in enhancing certain computational tasks, including pattern recognition and feature extraction. Integrating quantum techniques with classical models in medical imaging may help address challenges such as computational cost [7]. While some studies have already been published in the literature addressing similar problems, there are still gaps regarding the analysis of the quantum circuit depth and evaluations for applications more aligned with real-world scenarios.

This paper proposes a hybrid quantum-classical approach to breast cancer detection [1], specifically leveraging convolutions to enhance feature extraction and improve diagnostic accuracy. The contributions of this research include:

- **Hybrid Quantum-Classical Model for Tumor Classification:** Implementation of quanvolutions for feature extraction and classification of breast cancer images.
- **Analysis of Quantum Circuit Depth:** Assessment of circuit depth effects on classification performance and computational cost.
- **Evaluation of Image Resolution and Scaling:** Comparison of quantum-enhanced image analysis across different resolutions.
- **Scalability and Practical Application:** Comparison of hybrid quantum neural networks (HQNNs) with CNNs and discussion on quantum integration in medical imaging workflows.

The remainder of this paper is organized as follows. Section II reviews related works, and Section III provides the theoretical background associated with the proposed approach. Section IV introduces the proposed method, including the dataset, preprocessing steps, and the hybrid quantum-classical architecture for breast cancer detection. Section V details the materials and techniques used in the experiments, and Section VI presents the results, including performance evaluations and comparisons with classical approaches. Section VII discusses the findings' implications, potential limitations, and future research directions. Finally, Section VII states conclusions, summarizing key contributions and highlighting the potential of quantum-assisted models in medical imaging.

II. Related Works

Recent advances in hybrid quantum-classical architectures have introduced promising new directions for image classification by embedding quantum computing elements into traditional DL frameworks. A study by Henderson et al. [8] introduced the concept of **quanvolutions**, demonstrating their effectiveness on the MNIST benchmark. Their findings suggest that integrating quantum transformations into classical deep neural networks can improve feature extraction and, in some cases, improve classification performance. Building on this foundation, Matondo-Mvula and Elleithy [9] expanded the application of quanvolutions to medical imaging, specifically breast cancer detection using the BreastMNIST dataset (28×28). Their model utilized angle encoding to map ultrasound breast images into quantum states and employed a 9-qubit circuit incorporating specialized quantum gates to perform convolution-like operations. Their results showed that HQNNs can achieve competitive—and in some cases superior—performance compared to classical CNNs, demonstrating their potential for improving diagnostic accuracy in breast cancer detection.

Further extending this research, Xiang et al. [10] proposed an HQNN tested on the GBSG, SEER, and WDBC datasets, showing better classification performance compared to classical CNNs and logistic regression models. Their study emphasizes how quantum convolutional layers can improve model generalization, particularly in handling complex medical image data.

These studies suggest that quanvolutions can be an effective component in hybrid architectures, particularly for tasks such as breast cancer detection. While a definitive quantum advantage over traditional nonlinear transformations has yet to be established, the results indicate that such an advantage may emerge if quantum-derived features prove both valuable for classification and challenging to simulate with classical methods at scale. This makes the hybrid quantum-classical technique promising within the Noisy intermediate-scale quantum (NISQ) devices era. By incorporating quantum convolutional layers, these models demonstrate improved feature extraction, enhanced robustness against adversarial perturbations, and more efficient optimization strategies, contributing to advancements in medical diagnostic systems.

Although significant progress has been made, open questions must be addressed. The **depth of quantum circuits**, the **scalability** of these approaches, and their **applicability** to higher-resolution medical images remain areas that require further investigation. Further research is needed to understand the limitations and potential advantages of quantum-enhanced architectures and ensure their feasibility for practical use in medical imaging.

III. Theoretical Background

Deep learning stands at the forefront of advancements in breast cancer imaging, offering significant potential to improve diagnostic accuracy and enable better prognosis and response prediction. Among DL models, CNNs are widely used in medical imaging because they can automatically extract spatial features from image data. CNNs have been successfully applied to breast cancer detection, particularly in classifying mammograms, ultrasound images, and MRI scans with high accuracy [11].

A typical CNN architecture consists of convolutional, pooling, and fully connected layers, which work together to detect patterns and classify images. While these networks have advanced medical imaging analysis, their practical implementa-

[1]The implementation is openly available at https://github.com/yrsobrinho/BreastCancerQuanvolution

tion presents several challenges. Training deep CNNs requires substantial computational resources, increasing costs, especially for real-time applications. Additionally, their sensitivity to adversarial perturbations raises concerns about diagnostics reliability, as minor input image modifications can cause significant misclassifications. Another limitation is the restricted availability of medical imaging datasets, often constrained by privacy regulations, which affects the ability of models to generalize across different clinical scenarios.

These limitations have led to the exploration of alternative approaches, and quantum computing has emerged as a potential solution to address challenges in machine learning. Quantum-enhanced machine learning can improve generalization, efficiency, and feature extraction by employing quantum principles such as superposition and entanglement. The shift from classical to quantum computing may provide new computational capabilities, enabling the development of more advanced models capable of handling the complexities inherent in medical data.

Quantum computing introduces a fundamentally different paradigm of computation, leveraging quantum mechanical principles to perform calculations that may be infeasible for classical systems. Unlike classical computers that process binary information as definite 0s and 1s, quantum computers operate using **qubits**, which exploit quantum phenomena such as superposition, entanglement, and quantum measurement [12].

- **Superposition:** A qubit can exist in a linear combination of computational basis states $|0\rangle$ and $|1\rangle$, mathematically represented as follows:

  $$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle, \quad \text{where } |\alpha|^2 + |\beta|^2 = 1. \tag{1}$$

  This property allows quantum computers to process multiple possibilities simultaneously.
- **Entanglement:** When two or more qubits become entangled, their states become intrinsically correlated, regardless of spatial separation. Measuring one qubit instantaneously affects the state of its entangled counterpart.
- **Quantum Measurement:** Measuring a quantum state collapses its superposition into one of the basis states with probabilities determined by the squared magnitude of the probability amplitudes.

These properties enable novel computational models, particularly in optimization and machine learning, where quantum feature encoding and transformations can enhance pattern recognition. Since quantum computing is still in its early stages, its integration with classical machine learning has led to the development of hybrid architectures that strategically combine the strengths of both paradigms.

Among these approaches, parameterized quantum circuits (PQC) play a key role by introducing trainable quantum transformations that operate similarly to classical neural network layers. In a hybrid architecture, quantum computations are embedded within a larger classical framework, where quantum layers process data and extract features that may be challenging for classical models alone. The outputs from these quantum operations are then passed to classical layers, which handle further processing and classification. This combination allows models to use quantum properties while maintaining compatibility with established machine learning techniques and hardware, improving data representation and computational efficiency.

Quanvolutional networks extend the concept of convolutional layers in CNNs by introducing quantum transformations to extract features from classical data. First proposed for the MNIST dataset [8], quanvolutions operate as follows:

- **Quantum feature encoding:** Classical image patches are encoded into quantum states via quantum feature maps.
- **Parameterized quantum circuit:** A set of quantum gates processes these quantum states, transforming the encoded information.
- **Measurement and feature extraction:** The transformed quantum states are measured, and the extracted features are passed into a conventional CNN for classification.

Quantum feature maps enable quanvolutions to identify patterns in image data that classical filters might overlook. This is particularly relevant in medical imaging, where subtle differences in tumor structures can influence diagnosis. By incorporating quantum operations into feature extraction, quanvolutions enhance the ability to distinguish complex patterns in medical scans.

Since large-scale quantum neural networks remain impractical, quanvolutional networks offer a more feasible approach within the NISQ era. Rather than replacing classical CNNs, they function as quantum-enhanced filters, refining feature extraction while maintaining compatibility with existing DL architectures. This integration allows quantum computing to contribute meaningfully to medical imaging without requiring fully quantum models.

As quantum hardware advances, hybrid quantum-classical approaches like quanvolutions are expected to improve medical AI applications. Their ability to process imaging data with **greater precision** could support more accurate diagnostic models, particularly for complex cases where traditional methods struggle to capture subtle variations.

IV. Proposed Method

This work introduces a hybrid quantum-classical approach for breast cancer detection that leverages quantum-enhanced feature extraction through quanvolutional layers integrated into a DL pipeline. The methodology is designed to transform raw medical images into a feature-rich representation, thereby enhancing classification performance. Figure 1 illustrates the workflow of the proposed approach.

The first step involves **preprocessing** the medical images. Given an input image, we employ a partitioning strategy to divide it into smaller, non-overlapping patches of fixed size. This partitioning allows for individual analysis of **localized regions** of the image, facilitating the subsequent quantum processing. For grayscale images, we ensure consistency in processing by reshaping them appropriately, and each patch is converted into a vector representation, serving as the input for the quantum circuit.

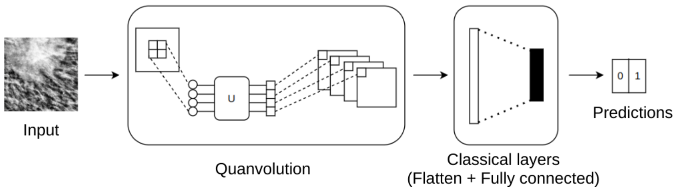

Fig. 1: Overview of the proposed hybrid quantum-classical model.

Once the patches are prepared, they are **mapped** to a quantum system where a PQC processes the data. This circuit includes several key components. Classical pixel values are initially encoded into quantum states using parametric rotational gates, allowing the circuit to process image patches while preserving crucial spatial information. Following, a sequence of quantum layers—comprising parameterized rotations (which induce arbitrary superpositions) and entangling gates—is applied, introducing complex, non-linear relationships between input features that classical CNNs struggle to capture. The quantum circuit then measures the expectation values of Pauli-Z operators, yielding a transformed feature representation for each patch.

To assess the performance of our approach, we evaluated three different circuit depths, denoted as depths 1, 2, and 3. Each type corresponds to a varying number of quantum logical gates, which affects the circuit's capacity to capture intricate patterns in the data. The specific configurations of these circuits are illustrated in Figure 2, where type 1 features a shallower circuit with fewer gates. In contrast, type 3 includes a deeper configuration to enhance expressive power. All circuits employ a four-qubit architecture, a design choice to balance expressive capacity with practical feasibility. Limiting the number of qubits reduces the computational overhead associated with quantum processing, making it **more compatible** with NISQ devices and future digital quantum computers.

After all patches have been independently processed through the quantum circuit, the transformed outputs are **reassembled** into a structured format, forming a feature map. This new representation is analogous to the output of a conventional convolutional layer but incorporates advantages from quantum-entangled representations, which encode correlations across multiple input dimensions simultaneously.

The quantum-processed feature maps are then passed into a DL model for classification. This process begins with applying a non-linear activation function, ReLU, to the quantum-transformed features, enhancing their expressivity. Subsequently, the features are flattened into a single vector and fed into a fully connected neural network. The final layer employs a log softmax activation function to produce a probability distribution across the target classes, distinguishing between benign and malignant cases.

By integrating quantum-enhanced feature extraction within a classical DL framework, this approach aims to improve the

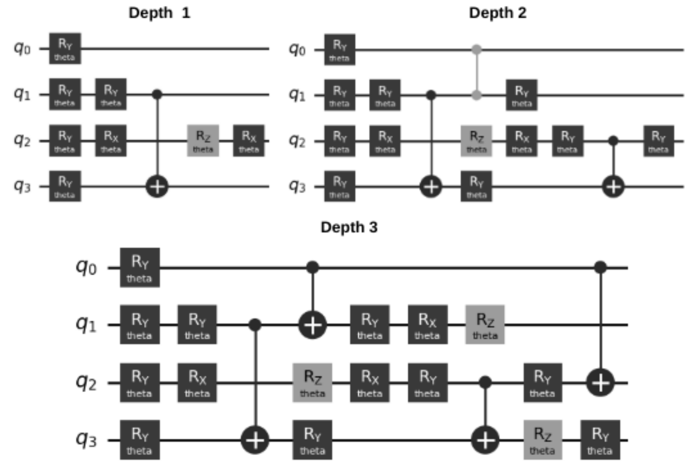

Fig. 2: Diagram of the circuit model, where "Depth 1," "Depth 2," and "Depth 3" represent the quantum circuits' depth tested in the proposed method. "Theta" denotes the fixed parameters in the rotation gates (RX, RY, RZ).

accuracy of breast cancer detection while ensuring computational feasibility for the early adoption of emerging quantum hardware. Using four-qubit circuits reduces resource demands, enabling the practical implementation of this method in current and near-future quantum hardware.

V. MATERIAL AND METHODS

The proposed application of HQNN in breast cancer classification is the central focus of this study. This approach incorporates a quantum convolutional layer into a DL framework to investigate whether quantum feature extraction can improve detection accuracy. To ensure reliable results, the model is rigorously evaluated across multiple datasets and varying circuit depths, while quantum simulations benefit from acceleration via GPU-based processing.

A. Datasets

Reliable medical imaging datasets are essential for training and validating classification models. This study utilizes BreastMNIST and BCDR (Breast Cancer Digital Repository), which contain breast ultrasound and mammographic images, respectively, enabling binary classification of malignant and benign cases.

BreastMNIST [13] consists of 780 grayscale ultrasound images in multiple resolutions (28×28, 64×64, 128×128 and 224×224), preprocessed for classification tasks. BCDR [14] provides annotated mammographic images with clinical metadata, supporting classification and segmentation. Lesion annotations guide the segmentation process, ensuring models focus on diagnostically relevant regions. Contrast-Limited Adaptive Histogram Equalization (CLAHE) enhances image contrast before resizing (64×64, 128×128, and 224×224) and normalization. After segmentation preprocessing, 293 images were obtained for classification. Figure 3 shows some preprocessed mammograms from BCDR and sample images illustrating variability in ultrasound data from BreastMNIST.

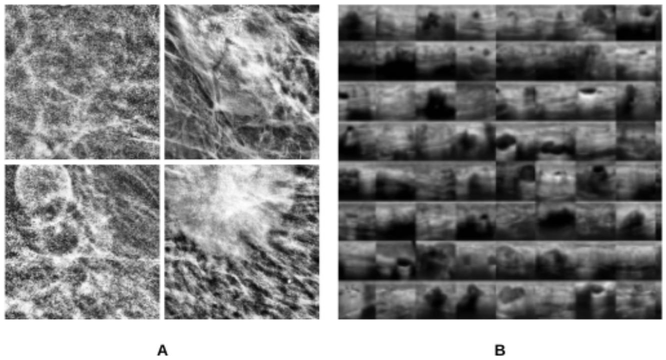

Fig. 3: Samples from segmented mammograms and ultrasound breast images extracted from (A) the BCDR and (B) BreastMNIST datasets, respectively.

B. Experimental Setup

Training quantum circuits on actual hardware presents challenges due to noise and limited qubit availability. Consequently, simulations are executed using a GPU-accelerated backend. The Lightning GPU device in PennyLane enhances the CPU-based Lightning Qubit simulator by integrating NVIDIA's cuQuantum SDK, enabling faster quantum state-vector simulations. This study is implemented in Python, using PennyLane for quantum computing and PyTorch for deep learning tasks. The quantum and classical architectures are trained on an NVIDIA RTX 4070 Ti SUPER graphics card to accelerate computational processes.

C. Training

The HQNN training procedure employs a cross-entropy loss function and the Adam optimizer with an initial learning rate of 0.01, which is adjusted every five epochs throughout 20 epochs. The classical architecture uses BCELoss and the Adam optimizer across 400 epochs on BreastMNIST and 1000 on BCDR for comparison purposes. A batch size of 32 is maintained to balance computational efficiency and memory constraints. To enhance generalization, data augmentation techniques such as random rotations and horizontal flips are applied during training.

The models' performances are assessed using a variety of evaluation metrics, including accuracy, precision, recall, F1 score, and the area under the receiver operating characteristic curve (AUC). These metrics provide a comprehensive view of the model's ability to accurately classify benign and malignant cases, thereby affirming the progress of the proposed HQNN approach and supporting comparisons with robust classical models.

VI. Results and Discussion

Tables I and II present the outcomes, offering a comparative analysis of quantum and classical approaches to breast cancer detection. Despite being limited to a 4-qubit PQC, the quantum model demonstrates competitive performance even at lower circuit depths, suggesting that quantum architectures can be implemented on NISQ devices and integrated into near-term mammography screening systems. The observed trends indicate that quantum enhancements contribute to feature extraction and classification without requiring deep circuits, aligning with the broader goal of developing hybrid quantum-classical models for tumor classification.

TABLE I: Classical models' performance for validation and test sets on different datasets. In this table, ”S” stands for small. The top-performing results are highlighted in bold.

BreastMNIST						
28x28						
Model	**Set**	**Acc**	**Prec**	**Recall**	**F1**	**AUC**
ResNet-18	**Val**	**78.2%**	**83.2%**	**78.2%**	**72.2%**	**90.6%**
	Test	**85.2%**	**84.9%**	**85.2%**	**85.1%**	**87.6%**
MobileNetV3 (S)	**Val**	74.1%	53.4%	73.1%	61b.7%	50.0%
	Test	76.3%	74.1%	76.3%	73.3%	76.7%
64x64						
ResNet-18	**Val**	**74.3%**	**81.0%**	**74.3%**	**64.3%**	**96.4%**
	Test	**91.0%**	**90.9%**	**91.0%**	**90.8%**	**89.9%**
MobileNetV3 (S)	**Val**	74.3%	81.0%	74.3%	64.6%	88.3%
	Test	87.8%	87.5%	87.8%	87.4%	88.1%
128x128						
ResNet-18	**Val**	**75.6%**	**81.7%**	**75.6%**	**67.3%**	**97.8%**
	Test	**92.9%**	**93.0%**	**92.9%**	**93.0%**	**94.4%**
MobileNetV3 (S)	**Val**	74.1%	53.4%	73.1%	61.7%	62.9%
	Test	86.6%	86.3%	86.6%	86.4%	88.6%
224x224						
ResNet-18	**Val**	**74.3%**	**81.0%**	**74.3%**	**64.6%**	**97.9%**
	Test	**89.1%**	**88.9%**	**89.1%**	**88.7%**	**92.7%**
MobileNetV3 (S)	**Val**	74.1%	53.4%	73.1%	61.7%	62.9%
	Test	87.1%	86.9%	87.1%	86.9%	89.9%
BCDR						
64x64						
ResNet-18	**Test**	**74.3%**	**84.3%**	**74.3%**	**76.5%**	**86.5%**
MobileNetV3 (S)	**Test**	62.8%	81.3%	62.8%	66.0%	88.1%
128x128						
ResNet-18	**Test**	78.57%	87.4%	78.5%	80.3%	91.5%
MobileNetV3 (S)	**Test**	**90.0%**	**89.6%**	**90.0%**	**89.5%**	**81.8%**
224x224						
ResNet-18	**Test**	75.7%	86.4%	75.7%	77.8%	92.9%
MobileNetV3 (S)	**Test**	**90.0%**	**92.0%**	**90.0%**	**90.5%**	**95.3%**

The ROC curve comparison presented in Figure 4 highlights the quantum model's adaptability across different image resolutions of the BreastMNIST dataset. The 28×28 and 224×224 resolutions achieved the best performance, with well-defined curves indicating a strong balance between sensitivity and specificity. While the 128×128 resolution remained competitive, it showed slight variability, suggesting diminishing returns beyond a certain threshold. The 64×64 resolution exhibited more significant fluctuations, pointing to inconsistencies in feature extraction. Although the classical model demonstrated a superior ROC curve, its convergence was less stable, and certain resolutions exhibited difficulties distinguishing classes during validation, even with a high number of training epochs.

TABLE II: Quanvolution's performance measures for validation/test or test sets on different datasets. The top-performing results are highlighted in bold.

BreastMNIST															
Circuit Depth	**1**					**2**					**3**				
						28x28									
	Acc	**Prec**	**Recall**	**F1**	**AUC**	**Acc**	**Prec**	**Recall**	**F1**	**AUC**	**Acc**	**Prec**	**Recall**	**F1**	**AUC**
Val	**87.2%**	**87.8%**	**87.2%**	**86.1%**	**85.4%**	85.9%	86.7%	85.9%	84.5%	80.0%	82.1%	83.2%	82.1%	79.3%	75.8%
Test	**82.1%**	**81.7%**	**82.0%**	**80.3%**	**82.6%**	81.4%	80.5%	81.4%	80.2%	81.2%	78.2%	76.7%	78.2%	76.7%	77.2%
						64x64									
Val	83.3%	84.4%	83.3%	81.1%	77.3%	86.0%	86.7%	86.0%	84.5%	86.0%	**80.8%**	**80.0%**	**80.8%**	**79.0%**	**78.5%**
Test	80.8%	80.6%	80.8%	78.2%	84.1%	78.2%	76.7%	78.2%	75.7%	80.7%	**82.1%**	**83.2%**	**82.1%**	**79.3%**	**81.6%**
						128x128									
Val	84.6%	84.6%	84.6%	84.6%	84.2%	**80.8%**	**79.7%**	**80.8%**	**79.4%**	**80.5%**	83.3%	82.7%	83.3%	82.6%	78.0%
Test	78.9%	78.2%	78.9%	78.4%	80.6%	**79.5%**	**78.9%**	**79.5%**	**79.1%**	**82.3%**	78.2%	76.8%	78.2%	77.0%	77.6%
						224x224									
Val	79.5%	78.3%	79.5%	78.3%	82.0%	76.9%	75.7%	77.0%	76.1%	75.4%	**82.1%**	**81.6%**	**82.1%**	**81.8%**	**79.8%**
Test	77.0%	76.3%	77.0%	76.5%	77.1%	73.7%	72.1%	73.7%	72.6%	77.4%	**80.1%**	**79.0%**	**80.0%**	**79.0%**	**81.1%**
						BCDR									
						64x64									
Test	**84.7%**	**87.2%**	**84.7%**	**81.0%**	**71.0%**	83.3%	82.8%	83.3%	79.8%	66.6%	80.6%	77.7%	80.6%	77.0%	61.1%
						128x128									
Test	**80.0%**	**77.6%**	**80.0%**	**74.3%**	**54.3%**	78.6%	74.6%	78.6%	74.8%	67.0%	70.0%	70.7%	70.0%	70.4%	64.5%
						224x224									
Test	67.1%	70.8%	67.1%	68.7%	66.8%	77.1%	69.3%	77.1%	70.7%	73.6%	**78.6%**	**76.2%**	**78.6%**	**76.9%**	**64.6%**

This suggests that the quantum models may offer better generalization capabilities, particularly in handling resolution variations. These results indicate that, although higher image resolutions come with increased computational costs, this does not necessarily lead to a decline in classification performance. The proposed model maintains strong performance even at higher resolutions, such as 224×224, that are commonly used with classical architectures without introducing significant computational penalties. Furthermore, classical architectures tend to enhance their performance as image resolution increases, benefiting from the additional spatial details available in high-resolution inputs. However, this improvement often comes at the cost of higher computational complexity and increased risk of overfitting, whereas the quantum model demonstrates robustness across multiple resolutions without a significant loss in performance efficiency. This indicates that, while resolution is an important factor, it does not represent a critical challenge to performance as long as an optimal balance between resolution and computational cost is maintained.

The analysis of circuit depth highlights its significant impact on the efficiency of quantum models. While **deeper** circuits generally **enhance** performance, they also introduce **greater computational** demands, emphasizing the importance of finding the optimal balance between circuit depth and computational efficiency. This trade-off can be addressed through continued research into quantum circuit optimization, enabling the realization of quantum enhancements without unnecessary computational overhead. Despite the simplicity of the circuit and the relatively shallow depths tested, the model still achieved strong performance, suggesting that effective results can be obtained even with modest circuit designs. This is particularly relevant for near-term quantum applications, especially as NISQ devices become more accessible. While current circuit designs remain limited, the performance observed in this study supports the feasibility of implementing quantum models in real-world medical applications, making such models a practical option shortly.

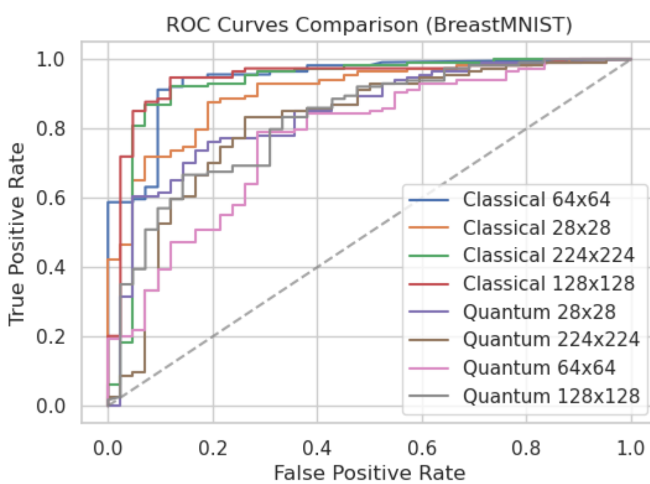

Fig. 4: Comparison of ROC curves for the best-performing circuit-depths and for ResNet-18 classical model across different image resolutions on the BreastMNIST dataset.

In contrast to quantum models, classical architectures like

ResNet and MobileNetV3 Small **are not directly comparable** to the hybrid quantum-classical model due to differences in the number of parameters, which affect the computational cost, memory requirements, and learning capacity. ResNet, for instance, leverages a larger parameter count for extracting complex features, whereas MobileNetV3 Small prioritizes efficiency. Similarly, the hybrid quantum-classical model operates under distinct constraints, such as limited qubit availability and circuit depth restrictions. This distinction highlights that the objective is **not to replace** classical computing but to develop models tailored to the unique constraints and opportunities of NISQ devices.

The comparative scalability of HQNNs and CNNs further supports discussions on integrating quantum computing into medical imaging workflows, positioning quantum computing as a complementary technology in this field. As research progresses and quantum devices become more capable, the hybrid model's potential for real-world medical applications will continue to grow, offering a promising avenue for enhanced diagnostic tools and more efficient processing in clinical settings.

Our best result with the hybrid quantum-classical model incorporating quanvolution demonstrates promising performance in breast cancer detection, with validation accuracy reaching 87.2% and an F1-score of 86.1%, indicating a well-balanced trade-off between precision (87.8%) and recall (87.2%). The test results, with an accuracy of 82.1% and an F1-score of 80.3%, suggest a degree of generalization, though there is room for improvement. The drop in AUC from 85.4% (validation) to 82.6% (test) indicates that refining circuit depth, optimizing quantum feature encoding, and incorporating better regularization techniques could further enhance robustness and mitigate potential overfitting.

VII. Conclusion and Future Works

The proposed quanvolutional architecture demonstrates competitive performance compared to more complex CNN-based models while maintaining a significantly more straightforward design. The method aligns with the constraints of NISQ devices and remains comparable to classical approaches in various evaluations. However, its simplicity increases training time for higher-resolution images, as the architecture lacks the optimizations present in more elaborate models. Additionally, the lack of accessible quantum hardware requires GPU-accelerated simulators. Another limitation is the limited availability of annotated medical imaging data. Although the quantum model demonstrated an ability to generalize with a relatively small dataset, access to more extensive and diverse datasets could further validate its effectiveness. Despite these challenges, the results indicate that the method effectively extracts relevant features, supporting its viability for early adoption in NISQ-era and next-generation digital quantum computers. Future research may explore its application to additional datasets and further investigate more advanced architectures incorporating trainable quantum parameters to enhance performance.

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