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Enhancing Diagnostic Accuracy for Breast Cancer Using Classical-Quantum Hybrid and Transfer Learning Technique

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Abstract

The need to have rapid technological solutions is becoming more evident as the information world digitizes and the amount of data around us grows. It is argued that the future of computational systems will be quantum computing, which will be faster and more capable of solving several issues that cannot be solved with current computers. The aim of the current research is to examine the contributions made by quantum transfer learning models in enhancing the detection of breast cancer. Although both classical and deep learning approaches have proved to be effective, they continue to face serious challenges in handling high-dimensional and complex medical data. Quantum computing can be a feasible solution to such complexity. This study presents a hybrid model, which combines a classical pre-trained deep learning model (ResNet50) with a range of variational quantum circuits- simple, entangled, and more complex. The main goal is to find the best model set up with regard to predictive power and computation time. It has been found that a hybrid model with an entangled variational circuit has an accuracy of 98.46, a precision of 100, and an F1-score of 97.3, which means a better result compared to the standard transfer learning model, which had an accuracy of 94.6, a precision of 97, and an F1-score of 90.4. These results improve upon recent quantum transfer learning studies, such as Azevedo et al. (2022) with 84% accuracy, and align closely with state-of-the-art quantum-optimized models reporting up to 99.3% accuracy, highlighting the effectiveness of our entangled variational approach on ultrasound images. Meanwhile, the traditional transfer learning model was the best in computational resource utilization.

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1. Introduction

Cancer, a disease that leads to the uncontrolled growth and spread of cells throughout the body, is known to have evolved nearly 200 million years ago [1]. Breast cancer has emerged as a major issue in recent years since this cancer type has a higher death rate than most others. In 2022, nearly 2.3 million people worldwide were diagnosed with cancer, leading to around 670,000 deaths [2]. Several factors have contributed to the increase in breast cancer occurrence. Firstly, environmental factors, such as chemical and radiation exposure, are possible causes of breast cancer. Secondly, lifestyle-related risk factors, such as inadequate and unhealthy nutrition, smoking, alcohol consumption, and a sedentary lifestyle, play a significant role. Moreover, hormonal factors include the early onset of menstruation, late menstruation, and the use of hormone replacement therapy. Genetic predisposition is connected to mutations in the BRCA1 and BRCA2 genes. Machine learning is a field of artificial intelligence where algorithms and models are designed to learn through data and independently produce decisions or predictions, and do not rely on explicit programming instructions. The use of machine learning algorithms has transformed the study of medical data, which makes it possible to use historical data to predict clinical outcomes. The kinds of algorithms are usually classified by supervised learning (SL) and unsupervised learning (UL) based on the type of learning paradigm they use.

Several strong supervised and unsupervised learning algorithms have been implemented to categorize labelled datasets of breast cancer. In supervised learning, the model takes information using previously labelled data and then uses the input data annotated with the correct outputs to produce predictions or decisions [3]. Supervised machine learning methods have been widely applied in the context of breast cancer to detect and classify the pathologies in medical images. The most widely used methods, which are applied under supervision, include support vector machines (SVM), decision trees, and deep neural networks, including convolutional neural networks (CNN). The concept of deep learning has had a significant impact on machine learning modelling due to its ability to perform better in a wide range of applications. Convolutional neural networks have delivered results that are impressive at times, sometimes beating the performance of experts when detecting cancer. These types of models are trained using large labelled image collections where the presence of malignancy has been confirmed using biopsy [4].

On the other hand, unsupervised learning does not require labelled data, but guides the model to detect patterns or structures within the data which was not directly supervised. In medical imaging, unsupervised learning is used to study and examine radiographic data. As an example, clustering algorithms may be used to divide the similar features and thus enable the demarcation of the cancerous tissues. Principal component analysis (PCA) is a supervised learning method, which is often used to reduce dimensionality, shrinking the number of features of multifaceted datasets and thus improving the analysis speed.

Although the traditional machine learning tool has been successful in many fields of application, such traditional methodologies still face significant challenges, especially in the medical field, where the cost of data handling is excessively high due to the sheer volume and complexity of clinical data. Further, the traditional algorithms require massive preprocessing of data and feature engineering to achieve the best performance [5]. The solution may be found in quantum computing. It could be possible to design robust technologies, using the peculiarities of quantum mechanics and changing the paradigm of modern computing.

Quantum Computing is an emerging field that utilizes the laws of quantum mechanics to solve excessively complex problems that current classical computers cannot [6]. Unlike classical computers, which utilize a small unit of information called a bit that can be either 0 or 1 to perform computation, quantum computers use quantum bits or qubits, which is a small unit of information for Quantum computer that can represent and store information in both 0 and 1 simultaneously due to the superposition nature of the atom, this has given quantum computers the ability to process a vast amount of possibilities simultaneously [7]. Another key quantum phenomenon used in quantum computing is entanglement, a phenomenon where two or more qubits are interconnected and correlated with each other, it's a type of correlation that cannot be classically defined, creating a quantum advantage that allows us to know the state of one qubit based on another entangled qubit state, regardless of the distance between them [8]. Exploiting quantum mechanics enables quantum computers to perform complex calculations much more efficiently than classical computers for certain types of problems. Quantum properties could significantly enhance cancer detection accuracy in high-dimensional data images. Although the potential of quantum computing is promising, quantum computing is still in its early stages, with many technical hurdles that need to be tackled, primarily focusing on enhancing the quantum processing unit (QPU) to scale the number of qubits while diminishing the error rates [9].

Questions started to arise about the potential of quantum computing in revolutionizing other computing branches when one of the most influential advancements made by Shor's algorithm in 1994 which demonstrated the power of quantum computers to factor large integers exponentially faster than any known classical algorithms and, Grover's algorithms the demonstrated quantum algorithms power in searching unsorted database [10], these two examples have proved the potential of quantum algorithms in certain problems. The success of several quantum algorithms necessitated us to reconsider integrating Quantum computing with other branches, one of which is AI [10]. Consequently, this has led us to a new emerging field, which is Quantum machine learning. This field is composed of combining two emerging technologies to utilize the power of both technologies. A systematic review of quantum machine learning in the biomedical domain found that quantum computing has shown a significant ability to process complex biomedical data ranging from drug discovery to diagnostic imaging and genetic research [11].

Diving deeper into a more Specific Quantum machine learning branch, the Quantum Neural network. Quantum Neural Network (QNN) is envisioned as a system that integrates the quantum theory properties with a Neural Network. According to one research, several purely quantum neural network model approaches have been proposed. However, bridging the gap between the nonlinear, dissipative dynamics of neural computing and the linear, unitary dynamics of quantum computing is a significant hurdle, and none of the approaches fully meet the criteria yet [11]. Recognizing the limitations of purely quantum models, recent research has proposed a novel approach to overcome the limitations of both purely quantum models and classical models. The proposed architecture is a hybrid model, where the classical neural network is integrated with quantum computing elements to harness the power of both disciplines. By applying a hybrid approach, we are addressing the issues of purely quantum models and enhancing the classical models to perform better on high-dimensional and complex data [12]. Future research might explore the potential of hybrid architecture and quantum circuit design for machine learning in the medical domain, such as early cancer detection, drug discovery, and more personalized treatments for patients.

Accurately predicting whether patients have breast cancer is crucial to patients; various resources, such as Ultra MRI scanners and other imaging techniques, have been allocated to optimize diagnostic results. Different machine learning algorithms have also been implemented to optimize the results. However, the traditional algorithms still have accuracy pitfalls and speed in detecting tumors. This study addresses the pitfalls of the previous machine learning and deep learning algorithms used in detecting breast cancer by proposing an Enhanced Classical-Quantum Hybrid and Transfer Learning Technique. This model combines the capabilities of Quantum computing and the available capabilities of pre-trained deep learning models to ensure efficiency in determining breast cancer tumors. Moreover, the research investigated the effectiveness of various Variational quantum circuits deployed to classify breast Cancer and evaluate the performance of our models/technique. This will contribute to patient outcomes, ensuring accurate diagnosis in a faster way. At the end of this research, we aim to find answers to the following questions:

How effective is the classical-quantum hybrid model using transfer learning and variational quantum circuits in classifying ultrasound breast image datasets compared to classical transfer learning?

What are the differences in terms of computational efficiency and model performance matrix between Quantum-classical hybrid models and classical transfer learning models for breast cancer detection on ultrasound images?

Considering the limitations of current quantum computing resources, what is the potential of Quantum-classical hybrid models running on classical hardware?

Test the hypothesis that the Hybrid Classical-Quantum model utilizing transfer learning on ultrasound breast images will demonstrate superior accuracy, sensitivity, and specificity in detecting breast cancer compared to traditional machine learning and deep learning models, despite the current limitations of quantum computing resources. The objective of this research is to compare and evaluate the effectiveness of quantum transfer learning to conventional transfer learning in classifying breast cancer on ultrasound images, to discover the most effective quantum network design for breast cancer classification problems on an ultrasound dataset, and to analyze and compare the efficiency of different models in terms of accuracy, sensitivity, specificity, and computational resource efficiency.

Nomenclature is included if necessary

$\|0\rangle$	Quantum ground state
$\|1\rangle$	Quantum excited state
H	Hadamard gate
R_y(θ)	Y-axis rotation gate with angle θ
CNOT	Controlled-NOT gate
CZ	Controlled-Z gate
$\otimes$	Tensor product
SQC	Simple Quantum Circuit
EQC	Entangled Quantum Circuit
AQC	Advanced Quantum Circuit
TL	Transfer Learning (ResNet-50)

θ_i	Rotation angle for qubit i
ϕ_i	Phase shift angle for qubit i
κ	Cohen's kappa statistic

1.1 Scope and Limitations of the Study

This paper aims to investigate the effectiveness of a Classical-Quantum hybrid model utilizing transfer learning on the ultrasound breast images dataset, compared to classical machine learning and deep learning models, for breast cancer detection. We seek to analyze and compare the efficiency of different models in terms of accuracy, sensitivity, and specificity, while also evaluating the real-world applicability of Quantum-classical hybrid models, considering the limitations of current quantum computing resources and the potential for future advancements.

The field of Quantum AI is still in the development stage. Despite the promising scope, several technical challenges are currently hindering the adoption and effectiveness of such a model [13]. Mainly due to the limitation in the current state of the existing quantum computers that are referred to as NISQ (noisy intermediate-scale quantum) devices [14], current quantum computers are susceptible to noise, which results in a high error rate and limited coherence time. Thus, this severely hinders the execution of complex quantum circuits [15]. Furthermore, the scalability challenges that are presented in terms of the number of qubits that the current quantum computers have and the complexity of quantum gates are also hindering the current quantum computers from performing large-scale projects [16]. Lastly, the task of encoding the classical data into a format that a quantum computer can process remains a major challenge. The encoding task must preserve the integrity of the original data while also preserving computational performance [17].

2. Literature Review

In this section, we will dive into the literature that has been done so far on machine learning, deep learning, and quantum machine learning techniques used for medical imaging and breast cancer detection.

2.1 Classical Machine Learning Techniques Used for Medical Imaging

Classical machine learning has been in use ever since electronic computers came into use in the 1950s and 1960s [18]. These very machine learning techniques were later used in medical imaging. Some of the common classical machine techniques that have been in use in medical imaging are:

Support Vector Machines (SVM): One study was done using SVM [19]. It showed that the technique had a lot of potential in breast cancer detection. Although SVM was good. They were limited to small datasets as larger datasets required time in breast cancer detection [20].

K-Nearest Neighbours (KNN): Another technique that has done well in breast cancer detection, as mentioned by different researchers, is optimized K-nearest neighbors (KNN). The study on optimized KNN has shown greater results with a performance of 94.35% [21].

2.2 Deep Learning and Transfer Learning in Medical Imaging

Deep learning and transfer learning have completely transformed the healthcare field in recent times. These advanced techniques have been found to perform excellently, especially in breast cancer detection. The most common deep learning technique that has been widely used is the Convolutional Neural Network (CNN) [22]. CNN has shown remarkable results in breast cancer detection by extracting meaningful features from the images and classifying the type of tumor. Nonetheless, CNNs that have impressive performances do come with some limitations. One of the major limitations is overfitting, which comes about when there is limited training data. CNNs are heavily parameterized models with millions of trainable parameters, thus increasing the chances of overfitting on training data and poor generalization on unseen data [23].

Transfer learning has emerged as a potent solution to address the limitations of deep learning models in training them. By leveraging pre-trained networks trained on large-scale datasets (such as ImageNet), transfer learning enables the re-use of learned features, significantly reducing the need for vast amounts of labeled medical data, especially in healthcare, where getting large amounts of data can be cumbersome and hard to obtain.

2.3 Quantum Machine Learning in Medical Imaging

Quantum machine learning is an emerging field with promising capabilities. Through the integration of quantum physics with machine learning, there's a hope to solve more complex problems, particularly in the healthcare domain, where data is more complex and higher in dimensionality.

Several research and quantum machine learning models have been adopted in the healthcare imaging sector. One research study discusses several quantum machine learning techniques that have been applied to different breast datasets. These include Quantum Neural Networks, Dimensionality Reduction Algorithms, and Quantum Support Vector Machines. QNN models [11].

A framework for classification tasks was introduced by a study that utilizes quantum circuits to transform classical data into quantum states [24]. His study demonstrated the potential of quantum-enhanced feature space to outperform classical classification methods on simple datasets but stressed the necessity for more advanced quantum hardware. Another study explored the use of quantum neural networks (QNN) for medical images, specifically classifying pneumonia and retina images [25]. The research studied two approaches: quantum circuits aiding classical neural networks and quantum orthogonal networks. Another researcher tried to employ supervised quantum machine learning for Iris classification on a Noisy Intermediate-Scale Quantum [26]. The result of the research showed a competitive outcome in comparison to classical models despite the current limitations of quantum hardware. Additionally, the research highlights the necessity to continuously create new quantum machine learning models as quantum hardware is evolving. A Nobel framework proposed a quantum framework for edge detection in medical images [27]. Their framework aims to encode the images into qubit information and apply quantum algorithms for edge detection. Their framework showed a significant speed-up in image processing, even with the limited capabilities of current quantum hardware.

2.4 Quantum Machine Learning for Breast Cancer Datasets

A new classical-quantum transfer learning algorithm to classify mammogram images was proposed in this study, which combined quantum computing with a deep learning algorithm to build a stronger classifier [28]. Different pre-trained classical deep-learning models were trained on a quantum circuit, and the quantum-enhanced models had an accuracy of 84 per cent., improving upon the 76.9 per cent. Percentage of purely classical methods.
Another study attempted to predict metastasis in lymph nodes of breast cancer and utilized quantum-inspired classifiers that were intended to imitate support-vector machines (SVMs). Such classifiers have been compared and contrasted with the classical CancerMath (CM) models. The quantum-based classifiers had accuracy and performance values reported between 59.5% and 69.5% and CM models showed between 61.7% and 67.4% in their values. The authors have concluded that the quantum classifiers showed a small edge in the ability to have sensitivity and specificity, which may boost their computational speed. However, the study compared the quantum-inspired approach to a single classical model, which restricted the overall validity of the results.

In another related work, quantum support vector machines (QSVMs) were implemented on the Wisconsin breast cancer data to help solve the issues that large-scale data processing may face [30]. In spite of the fact that the QSVM exhibited a shorter processing time, it was not able to systematically outperform its classical counterpart in terms of accuracy.

More recent research has provided further approaches to quantum machine learning in the diagnostics of breast cancer. Bilal et al. [36] proposed a quantum-enhanced extreme-learning machine (ELM) called BC-QNet, which builds on a Q-GBGWO optimization algorithm and FuNet transfer learning on the MIAS data set with an accuracy of 98.01 per cent on the malignant classes. A systematic review of quantum machine learning applications in breast cancer by Kaveh et al. [37] found an average area under the curve (AUC) of 0.91 with an accuracy of 90 per cent to 96 per cent among studies. Also, quantum-optimised strategy with Q-BGWO-SQSVM [38] using datasets like CBIS-DDSM achieved 99-percent accuracy, which highlights the advantage of quantum optimization as a feature extractor strategy.

An accuracy of 99% was obtained in the Q-BG Wo-SQSVM method [38], which used data sets such as CBIS-DDSM, which show that quantum optimization methods have the potential to be used in the extraction of features in breast cancer imaging.

2.5 Discussion

There is an ongoing effort to revolutionize the medical field through advanced technologies. The medical sector is also being revolutionized in an attempt to use new technologies in the field. Many machines and deep-learning algorithms have been successfully used in the field of healthcare and have shown significant overall performance. However, even traditional machine learning continues to face problems in the types of high-dimensional and complex data sets. Quantum machine learning is an exciting solution to improve classical models in dealing with such data, especially in the cancer detection domain. The potential that quantum properties provide can be utilized in future medical applications since it can provide capabilities that classical computing cannot. Regardless of the current hardware limitations of quantum computers, a number of investigations have investigated how quantum machine learning can be applied to breast cancer detection with promising outcomes. A classical-quantum hybrid model was applied to a dataset of breast mammograms (one of such studies) and showed the efficiency of applying an entangled quantum circuit with different pre-trained classical models [28].

Our research will seek to employ the classical quantum hybrid model framework that incorporates various quantum circuits with unique quantum computing characteristics to identify and categorize cancer in breast ultrasound imagery. We will compare and assess the performance of various models, classical transfer learning, and various quantum transfer-learned models, to determine the best arrangement with the highest accuracy and the experimental minimum computational power.

Table 1 summarizes key characteristics of related works, including methods, datasets, performance, and limitations.

Table 1 *Summary of related works on quantum machine learning for breast cancer detection*

Study	Year	Method	Performance	Limitations
Azevedo et al. [28]	2022	Classical-quantum transfer learning with pre-trained DL models and quantum circuits	84% accuracy	Limited to mammograms; lower accuracy compared to recent models; requires advanced quantum hardware
Pomarico et al. [29]	2021	Quantum-inspired classifiers vs. CancerMath models	59.5–69.5% accuracy for quantum classifiers	Compared only to one classical model, limited scope in capturing quantum advantages; lower performance metrics
Saini et al. [30]	2020	Quantum Support Vector Machines (QSVM)	Improved speed but inconsistent accuracy vs. classical SVM	Does not consistently outperform classical methods; limited to tabular data, not imaging
Bilal et al. [36]	2024	Quantum-infused ELM with FuNet transfer learning and Q-GBGWO optimization	98.01% accuracy for malignant classes; 97.75% sensitivity	Relies on annotated datasets; potential overfitting; not tested on diverse imaging modalities
Kaveh et al. [37]	2025	Systematic review of QSVM, QCNN, QNN	Avg. AUC 0.91; accuracy 90–96%	Review study, no original model; depends on the included studies' quality; lacks focus on ultrasound images
Bilal et al. [38]	2025	Q-BGWO-SQSVM with quantum optimization	99% accuracy; 98% sensitivity	Needs wider dataset validation; high annotation costs; potential overfitting with limited data

This table highlights that while recent works achieve high accuracy (up to 99%), they often rely on mammograms or tabular data, with limitations in hardware and dataset diversity. Our study addresses this by focusing on ultrasound images and comparing variational quantum circuits, achieving a competitive 98.46% accuracy with EQC.

3. Methodology

3.1 Research Design

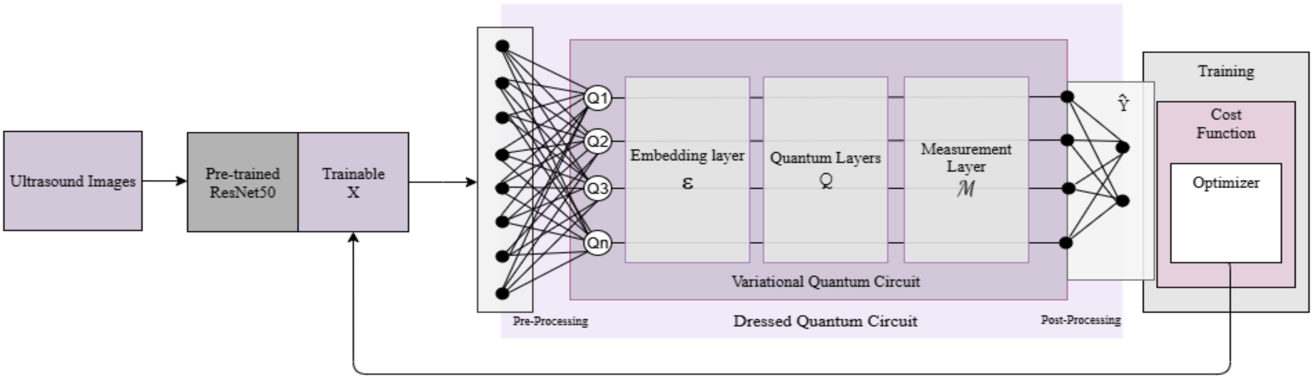

Fig. 1 *General architecture of the hybrid model, inspired by Altmann et al. (2023) [32] and adapted from Mari et al. (2019) [39]*

The architecture of the hybrid classical-quantum model, adapted from Mari et al. (2019) [39], is presented in Fig. 1. The model is tailored to classify breast cancer ultrasound images by integrating a pre-trained ResNet50 model with variational quantum circuits, including simple (SQC), entangled (EQC), and advanced (AQC) configurations. This study evaluates the effectiveness of these circuits in enhancing classification accuracy and computational efficiency compared to classical transfer learning, aiming to determine the most suitable model for breast cancer classification.

3.2 Data Collection and Preprocessing

This work uses a dataset of breast cancer ultrasound images [31]. The data set consists of medical images of breast cancer derived through the use of ultrasound scans on women who are aged between 25 and 75 years. It has 780 images with an average of 500 x 500 pixels in PNG format. Ground-truth images are also given with the original images. The images are divided into two sets, namely malignant and benign images, but further they have been divided into two groups: original images and masked images. The mask images outline areas of interest, e.g., tumors or lumps, thus providing ground truth over the original images. The method will improve the visualization of regions of interest and the training of models better.

A number of techniques were used in the preprocessing phase. The dataset was first prepared by superimposing the masked images on the original ultrasound images. This entailed checking the matching of every image with its mask, scaling the mask to the size of the original ultrasound image, and then overlaying and storing the resultant images in a different folder to augment them further. After the development of the overlaid dataset, several transformations and additions were made to improve the generalization of the models. The transformations were downsizing the images to 256 pixels, random horizontal and vertical flips, and random rotations and resized crops. Further modifications to the color and brightness were also done to enhance more on the image quality. Lastly, the images were standardized by adjusting pixel values to obtain an efficient training convergence with predefined values of mean and standard deviation.

In the last preprocessing step, the dataset was split into training and testing using a stratified sampling approach to maintain the distribution of the classes. Data loaders were utilized to feed the augmented images into the model during the training. Through these data pre-processing techniques, we ensured that the dataset was effectively prepared for further stages.

3.3 Classical-Quantum Hybrid Mode

3.3.1 The Classical Algorithms (Transfer Learning)

The architecture of the classical-quantum hybrid model will incorporate both classical transfer learning algorithms and quantum mechanics principles, hoping to enhance the capabilities of classical transfer learning. Based on Azevedo [28], using ResNet50 as a feature extractor for breast cancer problems demonstrated promising results. The model begins by feeding the input datasets into the classical pre-trained model, like ResNet (Residual Network) from the PyTorch library's torch vision. The ResNet50 model is leveraged to function as a feature extractor. To avoid retraining computational costs and preserve the pre-learned features, gradient freezing for all ResNet50 layers is employed. This is achieved by replacing the pre-training model's fully connected layer with a customized quantum circuit for training.

3.3.2 Variational Quantum Circuit

The integration between the classical and quantum circuits will be achieved through a dressed quantum circuit, where a classical pre-processing layer reduces the dimensionality of the classical transfer learning output to accord with the number of qubits in the quantum circuit. The quantum vectorized output will then be processed in the quantum variational circuits. The quantum variational circuit will transform an input quantum state $|x\rangle$ into $|y\rangle$, an output state, using an array of classical variational parameters w Eq (1) [17].

$$L : |x\rangle \rightarrow |y\rangle \text{ ; where } |y\rangle = U(w)\,|x\rangle \tag{1}$$

For the variational circuit to perform the transformation presented in Equation 1, the variational quantum circuit will perform three operations: data encoding, data manipulation, and measurement. In the first operation, the VQC will perform data encoding in the embedding layer denoted as ε in Fig. 1. The embedding layer will allow us to embed a real vector x into a quantum state $|x\rangle$ [17].

$$\varepsilon : x \rightarrow |x\rangle = E(x)|0\rangle \tag{2}$$

Variational quantum circuits manipulate data through a concatenation of quantum layers of depth q. Equation (3) represents the structure of a variational quantum circuit (VQC) of depth q, where each Li represents a quantum layer in the circuit, and the operation ∘ denotes the sequence of these layers [17].

$$Q = Lq \circ \dots L2 \circ L1 \tag{3}$$

The measurement layer, denoted as M, will extract the expected values of quantum results and convert them back into a classical output vector y, expressed as [17]:

$$M : |x\rangle \rightarrow y \; where \; y = \langle x\rangle \tag{4}$$

To sum up, the whole variational quantum net, including the measurement and the embedding component, can be represented as [17]

$$VQC = M \circ Q \circ \varepsilon \tag{5}$$

This study experiments with three variational quantum circuits—Simple Quantum Circuit (SQC), Entangled Quantum Circuit (EQC), and Advanced Quantum Circuit (AQC)—adapted from frameworks such as Mari et al. (2019) [39] and Barenco et al. (1995) [33], to identify the most effective quantum component for breast cancer classification. Each circuit, illustrated in Fig. 2, Fig. 3, and Fig. 4, employs angle encoding and distinct variational operations to process high-dimensional ultrasound image data.

```
0: ──H──RY(0.59)──RY(0.29)──RY(0.15)─┤  <Z>
1: ──H──RY(0.21)──RY(0.62)──RY(0.62)─┤  <Z>
2: ──H──RY(0.49)──RY(0.17)──RY(0.42)─┤  <Z>
3: ──H──RY(0.37)──RY(0.68)──RY(0.40)─┤  <Z>
```

Fig. 2 *Simple quantum circuit with 4 qubits and a quantum depth of 2*

Simple Quantum Circuit (SQC): This circuit consists of two main layers: a Hadamard Layer and a rotation Layer around the Y-axis. The Hadamard gate will set qubits into a superposition state, ensuring the system is unbiased. After initializing the qubits in a superposition state, the rotation layer will perform rotations on the Y-axis; these rotations will perform angle encoding on the input feature, encoding it into a quantum state. A series of variational rotations around the Y-axis will be repeated based on predefined quantum depth, allowing the circuit to adaptively learn from data. Finally, the circuit performs a measurement of the expected values.

The mathematical representation for the Simple Quantum circuit is as follows [33]:

$$SQC = \left(H \otimes^4 R_y(\theta) \otimes^4\right)^2 \tag{6}$$

The Hadamard gate begins by setting the qubits in a superposition state.

$$H|0\rangle = (|0\rangle + |1\rangle) / \sqrt{2} \tag{7}$$

Moreover, the rotation layer encodes the input feature into quantum states.

$$R_y(\theta)|0\rangle = \cos\left(\frac{\theta}{2}\right)|0\rangle + \sin\left(\frac{\theta}{2}\right)|1\rangle \tag{8}$$

Entangled Quantum Circuit (EQC): This circuit consists of three main layers. Just like the simple quantum circuit, this circuit has a Hadamard layer to set qubits in a superposition state and a rotation layer around the Y-axis to perform angle encoding, but additionally, it also has a C-NOT gate to create entanglement.

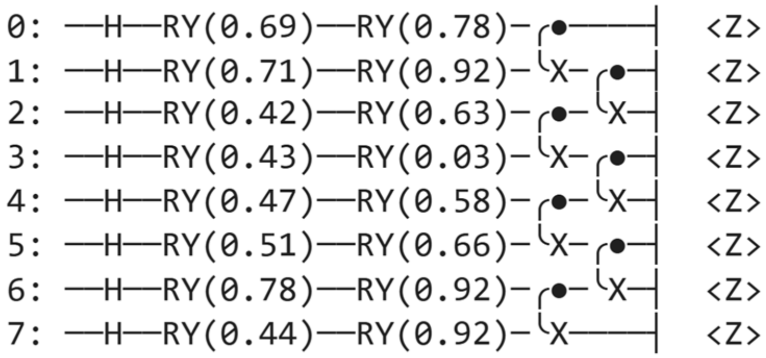

Fig. 3 *Entangled quantum circuit with 8 qubits and quantum depth of 1*

The mathematical representation of the entangled variational circuit for each pair of qubits (qi, qj) [33]:

$$\text{EQC} = \left(H^{\otimes^8} R_y(\theta)^{\otimes^8}\right) \prod_{(i,j)\in P} CNOT_{i,j} \tag{9}$$

Where the qubit initialization state is as follows

$$H|0\rangle = (|0\rangle + |1\rangle) / \sqrt{2} \tag{10}$$

Rotation Layer applied immediately after the Hadamard gate to encode the i-th input feature into the quantum state of qubit i

$$R_y(\theta_i)|0\rangle = \cos\left(\frac{\theta_i}{2}\right)|0\rangle + \sin\left(\frac{\theta_i}{2}\right)|1\rangle \tag{11}$$

Finally, CNOT Layer is applied to create entanglement between pairs of qubits

$$CNOT_{i,j}\left|x_i x_j\right\rangle = \left|x_i, x_j \oplus x_i\right\rangle \tag{12}$$

Advanced Quantum Circuit (AQC): This circuit integrates additional phase shift gates and controlled-Z gates, aiming to explore deeper quantum state spaces and more intricate entanglement patterns.

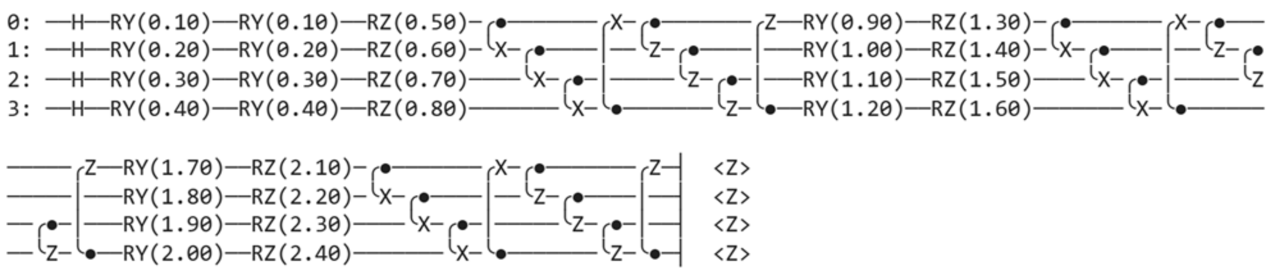

Fig. 4 *Advanced quantum circuit with 4 qubits and quantum depth of 3*

The Advanced quantum circuit mathematical representation for each qi with the additional phase shift can be represented as follows [33]:

$$\boxed{\text{AQC AQC} = \left[H^{\otimes 4}\, R_y(\theta)^{\otimes 4}\, R_z(\phi)^{\otimes 4} \prod_{k=0}^{2} CZ_{k,k+1} \right]^3}$$

Where

$$H|0\rangle = (|0\rangle + |1\rangle)/\sqrt{2} \tag{14}$$

$$R_y(\theta_i)|0\rangle = \cos\left(\frac{\theta_i}{2}\right)|0\rangle + \sin\left(\frac{\theta_i}{2}\right)|1\rangle, \quad where\ \theta_i = 2\arcsin\left(\sqrt{x_i}\right)$$

$$R_z(\phi_i)|0\rangle = e^{-\frac{i\phi_i}{2}}|0\rangle$$

$$\mathrm{CZ}_{i,j}\left|\mathrm{x_i x_j}\right\rangle = \mathrm{e}^{\mathrm{i}\pi \mathrm{x_i x_j}}\left|\mathrm{x_i x_j}\right\rangle$$

3.3.3 Dressed Quantum Circuit

To integrate the quantum circuit component with the classical transfer learning algorithm, a dressed quantum circuit forward approach was utilized to perform this connection in the hybrid approach. The forward method systematically manages the flow of data between classical algorithms and quantum networks by utilizing a classical preprocessing layer, quantum transformation, and classical post-processing layer. Mari et al. (2020) represented the dressed quantum circuit as follows [17]:

$$\text{DQC} = \text{L\_(nq}\rightarrow\text{n(out))} \circ \text{VQC} \circ \text{L\_(n(in)}\rightarrow\text{nq)} \tag{15}$$

The classical stage of the dressed quantum circuit involves classical preprocessing, where classical data is transformed to align with the quantum circuit requirements. The dressed quantum circuit linear layer will perform dimensionality reduction by linearly transforming the input feature to reduce the feature space to a manageable size for quantum processing [34]. This linear layer is often termed prenet. It compresses 2048 input features down to a smaller set of features equivalent to the number of qubits, n_qubits, available in the quantum circuit. The following step involves preparing features as angle parameters for the quantum gates by applying a hyperbolic tangent function to normalize those features.

The quantum processing stage will involve the variational quantum circuit. The variational quantum circuit will take the pre-processed feature from the previous stage to encode it into a quantum state and perform quantum computation on it. After quantum processing, the quantum state gets converted back into classical information. This is achieved by the measurement layer and another classical linear layer. In the post-processing stage, the quantum output will be mapped to the desired output dimensions; for binary classification tasks, it will be a two-dimensional output.

3.4 Training and Evaluation

For training the model, a hybrid architecture was employed, combining a pre-trained ResNet-50 model with a dressed quantum net. The ResNet-50 model served as a feature extractor, while the dressed quantum net performed quantum computations on the extracted features. The quantum net was implemented using Pennylane and Torch, utilizing layers of parametrized qubit rotations and variational quantum circuits. The training process

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involved freezing the ResNet-50 layers and replacing the fully connected layer with the dressed quantum net. Several hyperparameters were used to get the best outcome in this study. A few of them are optimizers that we applied to update the parameters of the model, specifically targeting the parameters of the quantum layer and a learning rate scheduler that dynamically adjusts the learning rate of the model. During evaluation, we use various metrics to assess performance. We used:

Accuracy: Calculated as the number of correctly classified images of any class.

$$Accuracy = \frac{\left(True\, positives\, (TP) + \, True\, negatives\, (TN)\right)}{(Total\, number\, of\, instances)} \tag{16}$$

Precision: Measure the rate of accurately classified instances of one class. It provides insights into how well the model identifies true positives compared to false positives.

$$Precision = \frac{True\, Positives\, (TP)}{\left(True\, Positives\, (TP) + \, False\, Positives\, (FP)\right)} \tag{17}$$

Recall: Measures the rate of actual positives that are acknowledged as positives by the classifier. It provides insights into how well the model identifies true positives compared to false negatives.

$$Recall = \frac{True\, Positives\, (TP)}{\left(True\, Positives\, (TP) + \, False\, Negative\, (FN)\right)} \tag{18}$$

F1 score: is a measure that combines precision and recall into a single metric. It provides a balanced assessment of a classification model's performance. The F1 score is calculated using the following formula:

$$F1\, score = \frac{(2 \times Precision \times Recall)}{(Precision + Recall)} \tag{19}$$

The F1 score ranges from 0 to 1, with 1 indicating a perfect model and 0 indicating poor performance. It is particularly useful in cases where both precision and recall are important, as it considers both metrics.

Matthews Correlation Coefficient (MCC): It is a classification accuracy measure for binary problems. It considers true and false positives and negatives and is considered a balanced metric even when classes greatly differ in size. The MCC ranges from -1 to +1. -1 means the prediction is not good, while +1 indicates good prediction results.

$$MCC = \frac{\left((TP \times TN) - (FP \times FN)\right)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{20}$$

Cohen's Kappa (Kappa): Kappa is a statistical measure of inter-rater reliability. It can be used with any pair of qualitative (categorical) items. Calculated as:

$$\kappa = \frac{(p_o - p_e)}{(1 - p_e)} \tag{21}$$

Where:
p_o is the relative observed agreement among raters (i.e., the actual agreement),
p_e is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category [35].

Area Under Curve (AUC): AUC represents a classification performance indicator at different threshold values. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) on the x-axis. The AUC curve can be interpreted below AUC = 1: Ideal model. The model correctly separates all positive and negative examples.
AUC = 0.5: Random predictor, no discrimination ability. The classifier could also guess the class label of a query instance randomly.

0.5 < AUC < 1: The model was able to distinguish the positive class from the negative class. The higher the AUC, the better (uncorrelated performance is 0.5).

4. Results and Findings

4.1 Performance Metrics

The performance of the classical transfer learning model (TL) and three quantum-classical hybrid models—Simple Quantum Circuit (SQC), Entangled Quantum Circuit (EQC), and Advanced Quantum Circuit (AQC)—was evaluated using accuracy, precision, recall, F1-score, Area Under the Curve (AUC), Matthews Correlation Coefficient (MCC), and Cohen's Kappa. As shown in Table 1, the EQC model achieved the highest performance, with an accuracy of 98.46%, precision of 100%, recall of 94.8%, F1-score of 97.3%, AUC of 99.7%, MCC of 96.3%, and Kappa of 96.2%. The SQC model followed with an accuracy of 96.92%, precision of 100%, recall of 89.7%, F1-score of 94.5%, AUC of 99.6%, MCC of 92.7%, and Kappa of 92.4%. The TL model recorded an accuracy of 94.6%, precision of 97%, recall of 84.6%, F1-score of 90.4%, MCC of 87%, and Kappa of 86.6%, with no AUC reported. The AQC model had the lowest performance, with an accuracy of 93.85%, a precision of 96.9%, a recall of 82%, an F1-score of 88.8%, an AUC of 99.2%, an MCC of 85.2%, and a Kappa of 84.6%.

As illustrated in Fig. 5, the performance metrics are visualized with 95% confidence bounds, highlighting the statistical reliability of the results. The EQC model's tight confidence intervals for precision and F1-score indicate robust performance in classifying breast cancer ultrasound images. In contrast, the TL model shows wider confidence intervals for recall, suggesting less consistency in identifying positive cases. These findings underscore the EQC model's superiority in handling high-dimensional medical imaging data.

Table 2 *Performance metrics for the four models: classical Transfer Learning (TL), Simple Quantum Circuit (SQC), Entangled Quantum Circuit (EQC), and Advanced Quantum Circuit (AQC)*

	TL	SQC	EQC	AQC
Accuracy	0.976	0.946	0.976	0.954
Precision	1.000	0.971	1.000	0.9714
Recall	0.923	0.846	0.923	0.8718
f1	0.960	0.904	0.960	0.9189
auc	0.982	0.986	0.984	0.9791
mcc	0.945	0.871	0.945	0.8893
kappa	0.943	0.867	0.944	0.886

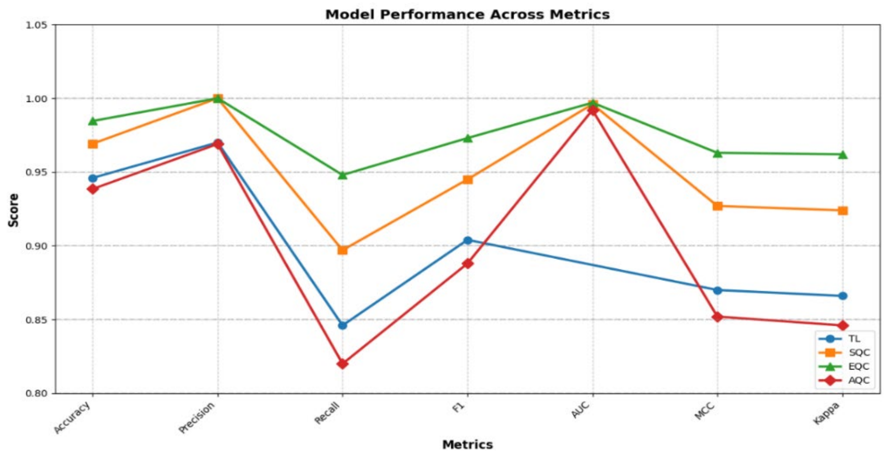

Fig. 5 *Performance metrics for classical Transfer Learning (TL), Simple Quantum Circuit (SQC), Entangled Quantum Circuit (EQC), and Advanced Quantum Circuit (AQC)*

4.2 Computational Efficiency

As presented in Table 3, the computational resources (Training Time, Inference Time, Memory usage, number of qubits, and the quantum depth of each circuit) of the models were evaluated for each model. The Experiment was conducted on a classical transfer learning model and three quantum-classical hybrid models, which were implemented using PennyLane to simulate quorons. The models include SQC (Simple Quantum Classifier), EQC (Enhanced Quantum Classifier), and AQC (Advanced Quantum Classifier).

Table 3 *The computational resources of the four models (TL, SQC, EQC, and AQC)*

	TL	SQC	EQC	AQC
Training Time(s)	143.9s	384.6s	502.8s	548.4s
RAM Usage (GB)	2.5	2.4	2.4	2.4
GPU RAM	3.6	0.9	0.9	0.9
Disk	30.8	28.2	28.2	28.2
num-epoch	10	15	15	15
Number of qubits	Nan	4	8	4
Quantum depth	Nan	2	1	3

Table 3 illustrates that simulating qubits on classical hardware was more resource-intensive than the classical ResNet model. This is primarily because of the complexity and resource demands of quantum simulation on classical hardware. This highlights the challenge of implementing quantum algorithms with the current classical capabilities. The table also shows how resource demands increase with more complex quantum circuits than with simple quantum circuits. Additionally, the hybrid models required frequent data encoding and decoding between quantum and classical states, which added more complexity and latency.

5. Conclusion

Both the classical and hybrid architectures, as shown in Table 2, are effective in classifying ultrasound imagery. The best result was the classical quantum hybrid model using an entangled variational quantum circuit, and an accuracy of 0.9846 and a precision of 1.0. SQC and AQC even showed competitive results using lower quantitative metrics with competitive accuracies of 0.9692 and 0.9385, respectively. All these findings indicate that hybrid models can be compared to classical ones in key performance indicators, which demonstrates their possible use in medical image classification.

On computational efficiency, ResNet took significantly fewer training steps but used a lot more GPU memory, suggesting that it efficiently utilize the available computational resources. The overall average time taken by ResNet to train was 3106.71 0.69.00s versus 6907.60 0.85351s for EQC, 9376.19 0.53281s for SQC and AQC. The performance measures (especially the EQC) of hybrid models were similar to ResNet, although the hybrid models had longer training times.

The quantum-classical hybrid model has significant potential in the given circumstances with the existing constraints of quantum computing capabilities. Although training of hybrid architectures is high, the performance measures verify its competitiveness. With the maturity of quantum hardware, such hybrid models can provide better performance and computational efficiency compared to traditional methods.

6. Significance of Study

The current study offers material contributions to the field of healthcare, especially on the issue of breast cancer diagnostics. Findings show that the hybrid classical-quantum models with different quantum architectures, i.e., SQC, EQC, and AQC, are equally valid to provide the same accuracy and precision levels as those that the classical transfer learning with ResNet 50 allows. These results highlight the promising nature of quantum machine learning in the field of medical imaging.

However, the experimental results also indicate that qubit simulation on classical hardware, as well as the encoding and decoding processes, is more computationally expensive, which increases the training and inference times. This finding highlights a critical issue that is relevant to the modern technology of quantum computing: the need to have easy access to quantum hardware and the limitations of emulating quantum circuits on classical computers.

Even though the potential of quantum machine learning is still strong, there is still much progress that needs to be made with regards to the availability of quantum hardware and the optimization of quantum algorithms. This paper shows the performance properties of various quantum circuits thus forming a very good foundation on what will be done later to optimize quantum algorithms and develop better quantum-classical hybrid models. The necessity of further development of quantum hardware, therefore, is obvious.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design****: Basheer Riskhan, Mehdi Gheisari, Siva Raja Sindiramutty;* ***data collection****: Bakari Salim Mahaba, Roua Alimam;* ***analysis and interpretation of results****: Basheer Riskhan, Roua Alimam, Bakari Salim Mahaba, Dua-e-Uswa, Siva Raja Sindiramutty;* ***draft manuscript preparation****: Dua-e-Uswa, Roua Alimam, Mehdi Gheisari. All authors reviewed the results and approved the final version of the manuscript.*

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