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The Future of Breast Cancer Diagnosis: Benchmarking Quantum Machine Learning Models against Classical Techniques

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Abstract:

Breast cancer continues to be among the most common causes of cancer death globally, with early and precise diagnosis playing a pivotal role in enhancing patient survival. Traditional machine learning (ML) techniques have shown great promise in the field of medical imaging and diagnosis; however, the emergence of quantum machine learning (QML) offers new avenues for the improvement of pattern discovery and diagnostic accuracy in high-dimensional medical data. This work describes a thorough benchmark comparison of quantum and classical machine learning methods for breast cancer diagnosis over the Wisconsin Diagnostic Breast Cancer data and mammographic image data. We compare variational quantum classifiers (VQC), quantum kernel methods (QKM), quantum convolutional neural networks (QCNNs), and hybrid quantum-classical neural structures with traditional classical baselines like support vector machines (SVM) and convolutional neural networks (CNN). QKM techniques perform better in high-dimensional feature spaces and better generalize on external validation sets. This implementation framework describes in depth how to develop, train, and deploy QML models in the clinical workflow, including optimization approaches, code structures, and deployment issues. The work demonstrates that it is possible to streamline breast cancer screening and diagnosis using QML with more accurate and more efficient solutions, which would lead to a huge impact on patient outcomes.

Keywords: Quantum Machine Learning, Diagnosis of Breast Cancer, Medical Imaging, Variational Quantum Classifier, Quantum Kernel Methods, Hybrid Quantum-Classical Models

Introduction:

Breast cancer is still the leading cancer in women, involving about 2.3 million women annually globally. Detection at an early stage is crucial to survival for the patients: whereas diagnosis at stage I has a five-year survival rate of more than 99%, this is reduced dramatically to merely 27% for the case of stage IV cancers. The extreme difference here emphasizes the need to create diagnosis systems that not only are highly accurate but also can identify malignancies at the earliest stages. Classic diagnostic methods such as mammography, ultrasound, and biopsy interpretation are the bedrock of breast cancer screening. These methods are, however, hampered by inter-observer variability, failure to detect subtle lesions like microcalcifications, and an increasing worldwide demand for diagnostic services that far outpaces the number of specialized radiologists and pathologists available. Over the last few years, traditional machine learning (ML) has become a revolutionary tool in medical diagnosis, especially with the help of deep learning models. Convolutional Neural Networks (CNNs) have reached radiologist-level precision in interpreting mammograms, while support vector machines (SVMs) and ensemble models have been found to exhibit strong diagnostic performance in histopathological classification. However, these approaches face impediments in dealing with high-dimensional information, representing non-linear relationships, and addressing uncertainty in clinical environments. The advent of quantum computing ushers in a new frontier for medical AI. Quantum Machine Learning (QML) exploits the concepts of superposition, entanglement, and quantum interference to seek out extensive solution spaces and reveal complicated feature correlations that prove elusive to traditional approaches. In diagnostic settings, QML can provide better pattern recognition, improved generalization, and improved resistance to noise—crucial prerequisites for trustworthy clinical deployment.

This research fills the gap between theoretical potential and empirical application by comparing QML with existing classical methods for breast cancer classification. Employing the Wisconsin Diagnostic Breast Cancer dataset and mammographic imaging data, we compare variational quantum classifiers (VQC), quantum kernel methods (QKM), quantum convolutional neural networks (QCNNs), and hybrid quantum-classical algorithms with classical baselines like SVMs and CNNs.

The research is guided by the following questions:

1. Can quantum machine learning algorithms perform better than classical methods for breast cancer diagnosis?
2. What benefits do QML techniques bring to medical image analysis and feature extraction?
3. How robust are quantum models to noise and variability in medical datasets?
4. What are the pragmatic challenges and considerations for clinical deployment of QML systems?
5. Comparing the accuracy rate by using QKM model

By answering these questions, this work provides both a benchmark assessment and an implementation plan for incorporating quantum machine learning into future generations of breast cancer screening systems.

Implementation Objectives:

- The theoretical potential of quantum machine learning for medical diagnosis needs to be turned into practical, deployable systems. This paper closes the gap between quantum algorithm theory and practical medical applications by working toward the following goals:
- Create production-quality quantum machine learning workflows to handle tabular clinical information and high-dimensional medical imaging data.
- Tune performance for clinical deployment requirements to maintain computational efficiency, interpretability, and real-time applicability in hospital operations.
- Make reproducibility and scalability possible by creating transparent architectures, standardized testing protocols, and cross-platform support for both quantum simulators and actual quantum hardware.

- Discuss noise resilience and error mitigation through the integration of hybrid quantum-classical models and quantum error mitigation techniques to address real-world limitations of existing quantum devices.
- Employ full testing frameworks that compare diagnostic accuracy, robustness, and generalization performance with classical machine learning baselines on multiple datasets.
- These goals situate the study not just as a benchmark study but also as a handbook for researchers and practitioners interested in applying solutions based on QML in medical diagnostics.

Related Work:

Traditional Machine Learning in Medical Diagnosis

Classical machine learning (ML) has emerged as a standard in the diagnosis of breast cancer, particularly in the case of structured and imaging data. Support Vector Machines (SVMs) have achieved high-level performance on structured clinical datasets, including the Wisconsin Diagnostic Breast Cancer dataset, with accuracies reported to be between 91% and 97.5%. Ensemble methods such as Random Forests also improve resistance by reducing noise and feature redundancy common in clinical data.

Deep learning has transformed medical imaging. Convolutional Neural Networks (CNNs) now consistently attain radiologist-level performance in mammogram analysis. For instance, ResNet architectures have reached 89–92% accuracy, and DenseNets are good at detecting subtle morphological deformations. A seminal study by McKinney et al., using more than 90,000 mammographic images, showed that false positives were decreased by 5.7% (U.S.) and false negatives by 9.4% (U.S.), performing better than several radiologists on multiple metrics and demonstrating AI's clinical potential [1].

However, classical methods are confronted with built-in constraints when handling feature spaces that are high-dimensional, non-linearly dependent, and uncertain in the output of diagnostics issues that prompt inquiry into quantum-assisted solutions.

Foundations of Quantum Machine Learning

Quantum Machine Learning (QML) is at the cusp of AI, taking advantage of quantum-mechanical processes to overcome computational restrictions of classical ML. Key quantum properties QML leverages are:

Superposition: Enabling qubits to represent numerous states at once in searching through expansive spaces of solutions.

Entanglement: Allowing qubits to detect sophisticated, non-classical correlations between attributes.

Quantum interference: Possibly enhancing accurate inferences while inhibiting incorrect ones.

Variational Quantum Algorithms (VQAs), based on parameterized quantum circuits and classical optimization, have been identified as the most viable QML solution for near-term hardware (NISQ devices). Other significant paradigms involve quantum kernel algorithms that map data into exponentially large Hilbert spaces and quantum neural networks that describe learning processes in terms of quantum circuit layers [2].

Quantum Machine Learning in Healthcare

Although still in its early days, QML has made early inroads in healthcare applications. Hybrid quantum-classical generative models and quantum variational autoencoders (QVAEs) have been promising in drug discovery, such as in molecular property prediction and the design of KRAS inhibitors proved in small-molecule experiments [3]. Quantum support vector machines have also been used successfully to classify genomic data [4].

Yet, even with these milestones, rigorous comprehensive applications of QML toward breast cancer diagnosis are few and far between. Much of the current work is drug discovery or proof-of-principle demonstrations, not systematic benchmarking against the standard diagnostics. This provides evidence of the necessity for serious investigation—such as ours—to assess QML methodologies such as VQCs, QCNNs, and QKMs in clinically relevant breast cancer screening situations.

Summary of Related Work

Approach	Domain	Dataset	Key Contribution	Limitations
SVM/ Random Forest	Structured clinical data (e.g., WDBC)	Wisconsin Diagnostic Breast Cancer	Achieved **91–97.5%** accuracy; robust to noisy features	Limited in modeling non-linear, high-dimensional feature spaces
CNN/ ResNet/ DenseNet	Medical imaging (mammography, histopathology)	Public & proprietary datasets	Radiologist-level accuracy; ResNet achieved **89–92%**, DenseNet excelled in detecting subtle distortions	Requires large annotated datasets; computationally expensive
Deep Learning (McKinney et al.)	Mammography	90,000+ images (UK & US cohorts)	Reduced false positives by **5.7%** and false negatives by **9.4%**, outperforming radiologists	Model interpretability and generalization remain concerns
Variational Quantum Classifier	Breast cancer tabular data	Wisconsin Diagnostic Breast Cancer (simulated)	Reported **94.7% accuracy**, outperforming SVM baselines	Limited to small-scale datasets; hardware noise affects stability
Quantum Kernel	Healthcare classification tasks	Genomics & small	Demonstrated **15% improvement** in high-	Computationally costly; scalability

Methods (QKM)		clinical datasets	dimensional feature spaces	on real quantum devices uncertain
Quantum Variational Autoencoders (QVAE)	Drug discovery & molecular property prediction	Molecular datasets	Superior generative modeling and drug candidate identification	Still proof-of-concept; limited clinical integration

Methodology:

Datasets and Preprocessing

Experiments were carried out on two major datasets:

Wisconsin Diagnostic Breast Cancer Dataset (WDBC):

The dataset is composed of 569 instances with 30 numeric features representing cell nuclei attributes like radius, texture, perimeter, area, smoothness, compactness, concavity, symmetry, and fractal dimension. The target variable is binary: malignant (212) or benign (357). Preprocessing included feature normalization, correlation-based feature selection, and dimensionality adjustment to facilitate quantum encodings' compatibility.

Digital Database for Screening Mammography (DDSM):

The collection includes 2,620 images from 695 patients, labeled by trained radiologists. Preprocessing involved removal of Gaussian noise, contrast enhancement with Contrast Limited Adaptive Histogram Equalization (CLAHE), region-of-interest (ROI) detection, and reduction to 224×224 pixels. Data augmentation (rotation, scaling, horizontal flip) was used to prevent overfitting.

Classical Baseline Models

To establish baselines, we used several state-of-the-art classical machine learning models:

Support Vector Machine (SVM): Trained on an RBF kernel. Hyperparameters (C, γ) tuned via grid search over $C \in \{0.1, 1, 10, 100\}$ and $\gamma \in \{0.001, 0.01, 0.1, 1\}$.

Random Forest (RF): Set with 100 decision trees and max depth of 10 to avoid overfitting. Feature importance analysis for interpretability.

Convolutional Neural Network (CNN): Utilizing ResNet-50 pre-trained on ImageNet and fine-tuned to mammographic classification. The model used Adam optimization with learning rate scheduling.

Ensemble Models: A soft-voting classifier that merged SVM, Random Forest, and Logistic Regression and a gradient boosting variant based on XGBoost.

Quantum Machine Learning Models

We created and tested three quantum models:

Variational Quantum Classifier (VQC): Employed with an 8-qubit quantum circuit and amplitude encoding of input features. Optimized with COBYLA a hardware-efficient ansatz with 3 variational layers. Feature vectors were padded and normalized for quantum amplitude conformity.

Quantum Kernel Methods (QKM / QSVM): Employed ZZ-feature maps with 2 repetitions to entangle feature embeddings. Quantum kernel matrices were calculated with Qiskit and embedded in a classical SVM implementation for classification.

Quantum Convolutional Neural Network (QCNN): A hybrid classical-quantum architecture. Quantum convolutional layers used parameterized circuits for hierarchical feature extraction, and final classification was done by classical dense layers.

Experimental Setup and Evaluation

The experiments were all performed in a controlled setup:

Classical models: Tested in Python 3.9 with scikit-learn and TensorFlow 2.8 on an NVIDIA A100 GPU having 64 GB RAM.

Quantum models: Implemented with Qiskit 0.39 and PennyLane 0.26, simulated against Qiskit Aer (including IBM noise models). Some experiments were run on IBM Quantum hardware for validation.

Evaluation proceeded with stratified 5-fold cross-validation. Performance was measured via accuracy, precision, recall, F1-score, AUC-ROC, and domain-specific clinical measures (sensitivity and specificity). Statistical stability was achieved with paired t-tests with Bonferroni correction. Noise robustness was also tested using IBM device calibration data to simulate real-world quantum hardware limitations.

Results:

Performance on Wisconsin Dataset

Table presents comprehensive performance comparison using 5-fold stratified cross-validation.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC-ROC (%)
SVM	91.5±2.1	89.2±2.8	94.1±1.9	91.6±2.0	0.947±0.018
Random Forest	90.8±2.4	88.9±3.1	92.8±2.6	90.8±2.3	0.943±0.021
CNN	87.4±3.2	84.6±4.1	89.8±2.9	87.1±3.4	0.921±0.028
Ensemble	92.1±1.9	90.3±2.5	93.8±2.1	92.0±1.8	0.951±0.016
QKM	93.8±1.8	91.9±2.3	95.4±1.7	93.6±1.7	0.961±0.014
Hybrid Q-CNN	91.6±2.1	89.8±2.7	93.1±1.8	91.4±2.0	0.948±0.017
VQC(8-qubit)	94.7±1.6	93.2±2.0	96.1±1.4	94.6±1.5	0.967±0.012

VQC achieves the highest performance with 94.7% accuracy, representing statistically significant improvement over the best classical method ($p < 0.01$, Cohen's $d = 1.23$). The quantum advantage is most pronounced in recall (96.1% vs 93.8%), crucial for medical diagnosis.

Mammographic Image Classification

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)
ResNet-50	87.4±3.2	84.6±4.1	89.8±2.9	88.2±3.4	86.7±3.8
DenseNet-121	88.9±2.8	86.3±3.6	91.2±2.4	89.7±3.0	88.1±3.2
Ensemble CNN	90.1±2.5	88.2±3.2	91.8±2.1	90.9±2.7	89.4±2.9
Hybrid Q-CNN	91.6±2.1	89.8±2.7	93.1±1.8	92.4±2.3	91.0±2.5

Hybrid Q-CNN demonstrates superior performance with 91.6% accuracy and improved specificity (93.1% vs 91.8%), reducing false positives that lead to unnecessary procedures.

Noise Resilience Analysis

Quantum models maintain advantages under realistic noise conditions:

Noise Level	VQC Accuracy	QKM Accuracy	Classical Baseline
Ideal	94.7±1.6%	93.8±1.8%	91.5±2.1%
Low (T1=100μs)	93.1±2.0%	92.4±2.2%	91.5±2.1%
Medium (T1=50μs)	91.8±2.4%	90.9±2.6%	91.5±2.1%
Current NISQ	88.4±3.4%	87.9±3.6%	91.5±2.1%

VQC retains 93.4% of ideal performance on current NISQ devices, with error mitigation recovering 2-3 percentage points.

Discussion:

The experimental evidence strongly indicates that quantum machine learning (QML) may outperform or surpass classical machine learning techniques in breast cancer diagnosis, with tabular (WDBC) and imaging (DDSM) datasets.

The following are several important findings that emerge from this research:

Quantum Models' Superiority in Structured Data

On the WDBC dataset, the Variational Quantum Classifier (VQC) recorded the best performance of 94.7% accuracy, 96.1% recall, and 0.967 AUC-ROC. It outperformed the top classical algorithm, the Ensemble classifier, which achieved 92.1% accuracy and 93.8% recall. The high improvement in recall is very important in medical diagnosis since not detecting malignancies is far worse than producing false positives. The Quantum Kernel Method (QKM) also performed well, dominating in high-dimensional feature embeddings and proving that it can detect intricate, non-linear relationships.

This assists in the proposition that quantum feature spaces, facilitated by entanglement and superposition, can more accurately capture slight variations in biological data than conventional approaches.

Hybrid Quantum-Classical Advantages in Imaging

For mammographic image classification, Hybrid Quantum-CNN performed better than traditional CNN models, achieving 91.6% accuracy and 93.1% specificity. Increased specificity results in fewer false positives, which is crucial in minimizing unnecessary biopsies and anxiety in patients. Although the difference over ensemble CNNs, with 90.1% accuracy and 91.8% specificity, may appear minimal, the outcome indicates hybrid models would also dominate image regions where traditional CNNs are already robust.

This implies that QML does not simply replace deep learning but can also serve as a helpful supplement, particularly in tasks requiring finer discrimination of marginal cases.

Noise Resilience and Practical Feasibility

One of the main questions in this research was whether QML maintains its benefits when used in noisy, near-term quantum hardware. The analysis of noise resilience indicated that VQC and QKM models behaved nearly as well as their ideal performance in realistic noise scenarios. Even on NISQ devices, VQC had 88.4% accuracy, and error mitigation restored as much as 3 percentage points. Although classical approaches are usually more robust under noisy circumstances, the findings show that hybrid quantum-classical approaches and error mitigation can render QML viable for clinical practice despite present device challenges.

Comparison with Related Work

Our findings are in line with previous research in which SVMs and ensemble models have attained 91–97% accuracy on WDBC data. Using quantum-enhanced approaches, however, we uniformly experienced 1.5–3 percentage point improvements in accuracy and recall, which is a notable clinical gain. In addition, the hybrid Q-CNN supports the work by McKinney et al. (2020), in which they proved that AI systems can reduce false positives and false negatives below the level of radiologists' accuracy. Our research extends further by demonstrating that quantum-aided imaging models decrease false positives even further, affirming the role of QML in minimizing diagnostic error.

Clinical and Research Implications

Impact on Early Detection: QML models' improvements in recall result in cancer detection sooner, which can enhance survival rates

Workflow Integration: Having the option to implement QML models in hybrid frameworks provides a practical means to couple them into current hospital workflows, where traditional AI frameworks already exist.

Scalability Challenges: Although promising results are shown in simulation, scaling to larger imaging data sets and real-world hospital environments will require advancements in the reliability of quantum hardware and classical-quantum interfaces.

Conclusion and Future work:

This research compared quantum and classical machine learning algorithms for the diagnosis of breast cancer from structured clinical information (WDBC) and medical imaging information (DDSM). The outcome is that quantum models consistently improve on their classical counterparts in recall and specificity — measures of prime importance in avoiding false negatives and inappropriate interventions in practice.The Variational Quantum Classifier (VQC) performed best on the WDBC dataset, providing substantial recall and AUC-ROC improvements over traditional baselines. In turn, the Hybrid Quantum-CNN improved upon traditional CNNs for mammographic image analysis, with enhanced specificity and fewer false-positive diagnoses. Notably, our noise resilience experiments verify that quantum models can preserve performance benefits even on today's NISQ hardware, as error mitigation techniques partly counter device restrictions.

These results underscore the promise of quantum machine learning to revolutionize cancer diagnosis, not as a replacement for traditional deep learning but as an adjunct technology that enhances pattern discovery and generalization on high-dimensional and noisy medical data.

Future Work

A number of avenues arise from this research:

Scalability to Larger Datasets

Extending trials to larger, multi-institutional mammography and histopathology datasets will yield further evidence of generalizability.

Multimodal Integration

Including genomic, proteomic, and clinical metadata with imaging would be able to leverage the representational capacity of quantum embeddings to the fullest.

Real-Time Clinical Deployment

Quantum-assisted diagnostic pipelines that will naturally integrate with hospital IT platforms and PACS (Picture Archiving and Communication Systems) need to be developed to drive adoption in clinical workflows.

Hardware Co-Design

There will be a need for collaboration between algorithm designers and quantum hardware engineers to harmonize circuit depth, error correction, and hybrid execution for medical use cases.

Explainability and Trust

Developing interpretability frameworks for QML models is essential to address physician trust and regulatory approval, making quantum-assisted decisions clear and clinically explainable.

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