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Investigating the Application of Quantum Machine Learning in Breast Cancer: A Systematic Review

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ABSTRACT

Background: Breast cancer diagnostic data is complex and accompanied by noise. Quantum machine learning can enhance the accuracy, efficiency, and scalability of artificial intelligence algorithms and has applications in various fields such as drug discovery and personalized medicine.

Methods: In the systematic review conducted, the databases PubMed, Embase, Scopus, and Web of Science were searched in December 2024. The search strategy included the keywords "Breast Cancer," "Artificial Intelligence," and "Quantum machine learning" along with their synonyms in article titles. Descriptive, qualitative, review, and non-English studies were excluded. The qualitative evaluation of the articles and the assessment of their bias were determined based on the Joanna Briggs Institute (JBI) indicators checklist.

Results: Twenty-nine studies utilizing artificial intelligence models for personalized breast cancer management were selected. Seventeen studies employing various deep learning methods achieved satisfactory results in predicting treatment response and prognosis, effectively contributing to the personalized management of breast cancer. Twenty-six studies demonstrated that machine learning methods could enhance the processes of classification, screening, diagnosis, and prognosis of breast cancer. The methods most frequently used in modeling were quantum support vector machine (QSVM), quantum convolutional neural network (QCNN), and quantum neural network (QNN), with an average AUC of 0.91. Additionally, the average accuracy, sensitivity, specificity, and precision indices of the models ranged from 90% to 96%.

Conclusion: Quantum computing can address some challenges arising from the increasing complexity and size of artificial intelligence models. Overall, the combination of artificial intelligence and quantum computing can significantly accelerate the drug discovery process and the development of effective drugs.

INTRODUCTION

Breast cancer is a common disease among women worldwide.[1] Early diagnosis of this disease is crucial for effective treatment and increased patient survival. Mammographic images are a common screening method for breast cancer.[2,3] Breast cancer screening requires a thorough visual examination to detect any signs of a mass, and ultrasound alongside mammography increases diagnostic sensitivity.[4] In a standard clinical examination, a radiologist reads the

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mammogram and classifies the findings based on the American College of Radiology's Breast Imaging Reporting and Data System (BI-RADS) vocabulary.[5]

If an abnormal finding is shown in digital mammography, it usually requires diagnostic work, which may involve performing three-dimensional mammography along with other imaging techniques.[6] If a lesion is suspected to be cancerous, further evaluation with a biopsy is recommended. Analyzing these images is challenging due to limited sensitivity, device or environmental noise, and the subtle differences between lesions and the background fibroglandular tissue, as well as various types of soft and hard lesions.[7] Sometimes, human vision’s ability to process images is limited, leading to false-negative rates in mammographic images.[8] Therefore, properly enhancing mammographic images through masks in deep learning techniques can help doctors accurately diagnose the disease.[9]

Breast cancer diagnosis for providing personalized treatment involves various dimensions. To increase accuracy and reduce false-positive and false-negative diagnoses in imaging and biopsy stages, recent advances in artificial intelligence (AI) have been used to develop systems that can assist doctors in clinical practice.[10,11] Therefore, in a precise diagnostic process, various factors such as image quality, radiologist and oncologist expertise, breast structure complexity, and the noise level of the imaging device used impact the accuracy of this disease's diagnosis. Developing decision support systems with advanced and new methods capable of handling noisy data is helpful.[12,14] Although classical machine learning is widely used and shows great potential in analyzing medical images, challenges of inadequate data labeling and slow processing speed still exist. Quantum machine learning (QML) can have a transformative effect on computer science and health. Using quantum techniques in classical machine learning can lead to better performance, reduced noise, higher speed, and shorter response times.[15,18] Since all studies have focused on classical AI methods in analyzing breast cancer data, we decided to explore the applications of QML in analyzing breast cancer data. This is because it can help in accurately and early diagnosing breast cancer through increased processing speed and efficiency, reduced data noise, reduced error rates, and ultimately reduced treatment costs.

Traditional machine learning algorithms usually require a large number of computational resources to solve complex problems. For large problems with enormous data, the processing time increases dramatically. The devices and hardware required to implement traditional algorithms are usually available, and it is now easy to use conventional processors or even graphics processing units (GPUs) to accelerate the calculations. Traditional algorithms often struggle at large scales. Processing large amounts of data requires a considerable amount of time and resources. By using quantum properties such as synergy and interference, some problems can be solved faster. But in practice, the development of quantum algorithms for complex problems still brings challenges such as noise reduction and the need for advanced hardware. In QML, many algorithms are still being developed in quantum machine learning. Different qubits may have applications, but their widespread use for various problems is still limited, and their efficiency is not fully proven compared to traditional machine learning.

Considering the capabilities of QML and the large volume of breast cancer medical data, this study was designed to investigate the algorithms used to analyze breast cancer data in order to create a perspective and help researchers in conducting future research.

METHODS

This study is a systematic review conducted in accordance with the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) 2020 guidelines.[19] In evidence-based medical research, the formulation and design of research questions are critical components for doing a study and providing answers.

Eligibility Criteria

SPICE, similar to PICO, is a useful tool for formulating focused clinical questions and conducting qualitative reviews.[20] SPICE stands for Setting, Perspective, Intervention, Comparison, and Evaluation, and it provides a framework for developing practice questions to find evidence in existing research. SPICE may be more suitable for formulating our research questions: (i) Setting: all publications worldwide; (ii) Perspective: patients and healthcare providers; (iii) Intervention: QML techniques; (iv) Comparison: only covers the breast cancer patient population; (v) Evaluation: how effective are QML techniques in evaluating breast cancer data?

Inclusion Criteria

Studies meeting all the following criteria were included in the review: (1) studies related to breast cancer; (2) application of one of the QML techniques; (3) performance evaluation of the techniques based on AI evaluation metrics; (4) articles written in English.

Exclusion Criteria

The exclusion criteria were as follows: (1) studies that were systematic reviews or meta-analyses; (2) book chapters and systematic articles; (3) studies using classical machine learning techniques; (4) articles without full English text available.

Information Sources and Search Strategy

A systematic search was conducted in electronic databases including Web of Science, MEDLINE (via PubMed), Scopus, and IEEE to identify relevant studies published over a 7-year period from early 2017 to December 1, 2024. Additionally, we searched the Embase database until January 10, 2024. The search strategy used in this study included a combination of keywords and Medical Subject Headings (MeSH) terms related to "Quantum Machine Learning" and "Breast Cancer." Table 1 shows the complete list of keywords and terms used in the search strategy for the Scopus database. A reference management software (EndNote X8, Thomson Reuters) was also used to collect references and eliminate duplicates.

Study Selection

The titles and abstracts of identified articles were independently screened by two authors of this study (ZK and SS). Full texts of potentially relevant articles were retrieved and reviewed if deemed relevant by both reviewers. Any disagreements between reviewers were resolved through discussion with a third investigator. The screening process followed the PRISMA 2020 methodology and is illustrated in Figure 1. Two authors (ZK and SS) analyzed and synthesized the main features of the selected articles and extracted the primary details. The first author (SS) evaluated the extracted information and verified the key elements.

Data Collection Process

The primary reviewer (ZK) collected the necessary information from the selected studies. A second reviewer (SK) then verified the accuracy of the accumulated information. Any disagreements were reviewed and resolved by a third reviewer (SS). The main data elements and characteristics of the selected articles are displayed in Table 1.

Study Bias Risk

The Joanna Briggs Institute (JBI)[21] critical appraisal checklist for analytical cross-sectional studies was used to assess the risk of bias in the studies (Figure 5). The goal of this assessment was to evaluate the methodological quality of the studies, consisting of 8 questions as follows: (1) Were the inclusion criteria clearly defined? (2) Were the study subjects and setting described in detail? (3) Was the exposure measured in a valid and reliable manner? (4) Were objective and standard criteria used for measuring the conditions? (5) Were confounding factors identified? (6) Were strategies to deal with confounding factors stated? (7) Were the outcomes measured in a valid and reliable way? (8) Was appropriate statistical analysis used?

These questions can be answered with 4 options: yes, no, unclear, and not applicable. Each "yes" response corresponds to 1 point, and if 70% of the questions in a study are answered "yes," the risk of bias is considered "low." If 50% to 69% of the questions are answered "yes," the risk of bias is "moderate," and less than 50% is considered "high risk".[16] The checklist was completed by 2 authors (ZK and SK), and any disagreements between the authors were resolved through discussion with a third author (SS).

RESULTS

The systematic review identified 29 studies that applied AI models to personalized breast cancer management. Of these, 17 studies employed various deep learning methods that yielded favorable results in predicting treatment responses and patient prognosis. The application of these models has been particularly effective in improving diagnosis and personalized treatment for breast cancer patients (Figure 2).

Two studies that used neural networks and clustering methods showed strong results in predicting patient survival and classifying breast cancer tumors. Meanwhile, one study successfully implemented transfer learning to predict treatment response, further contributing to the potential of AI in clinical applications.

Additionally, quantum machine learning techniques, such as quantum support vector machines (QSVM) and quantum neural networks (QNN), were highlighted as being particularly promising. These approaches demonstrated enhanced performance in analyzing complex and noisy data, with potential improvements in processing speed, accuracy, and error reduction compared to traditional machine learning methods. Quantum convolutional neural networks (QCNN), for example, achieved an accuracy index of 100% in certain diagnostic imaging tasks (Figure 3).

Further, studies utilizing quantum transfer learning and quantum kernel methods revealed their potential in improving the diagnostic precision of complex imaging data, as exemplified by accuracy scores exceeding 95% in several studies. Quantum techniques also facilitated rapid analysis of genomic and multi-omics data, effectively reducing noise and improving feature extraction processes. This capability is crucial in identifying critical biomarkers for early detection and personalized planning in breast cancer.

Table 1. Vocabulary Search Formula in Databases

Search MeSH terms and formula
I: (Breast Cancer OR Breast Neoplasm OR Breast Tumor* OR Malignant Neoplasm of Breast OR Breast Malignant Tumor* OR Breast Carcinoma* OR Diagnosis OR Prediction) II: (Quantum Machine Learning OR Deep Learning OR Machine Learning OR Unsupervised Machine Learning OR Supervised Machine Learning) Search strategy: I AND II PubMed: ("Breast cancer OR Breast Neoplasm OR Breast Tumor* OR Malignant Neoplasm of Breast OR Breast Malignant Tumor* OR Breast Carcinoma* diagnosis OR prediction") AND ("Quantum Machine Learning OR Deep Learning OR Machine Learning OR Unsupervised Machine Learning OR Supervised Machine Learning")

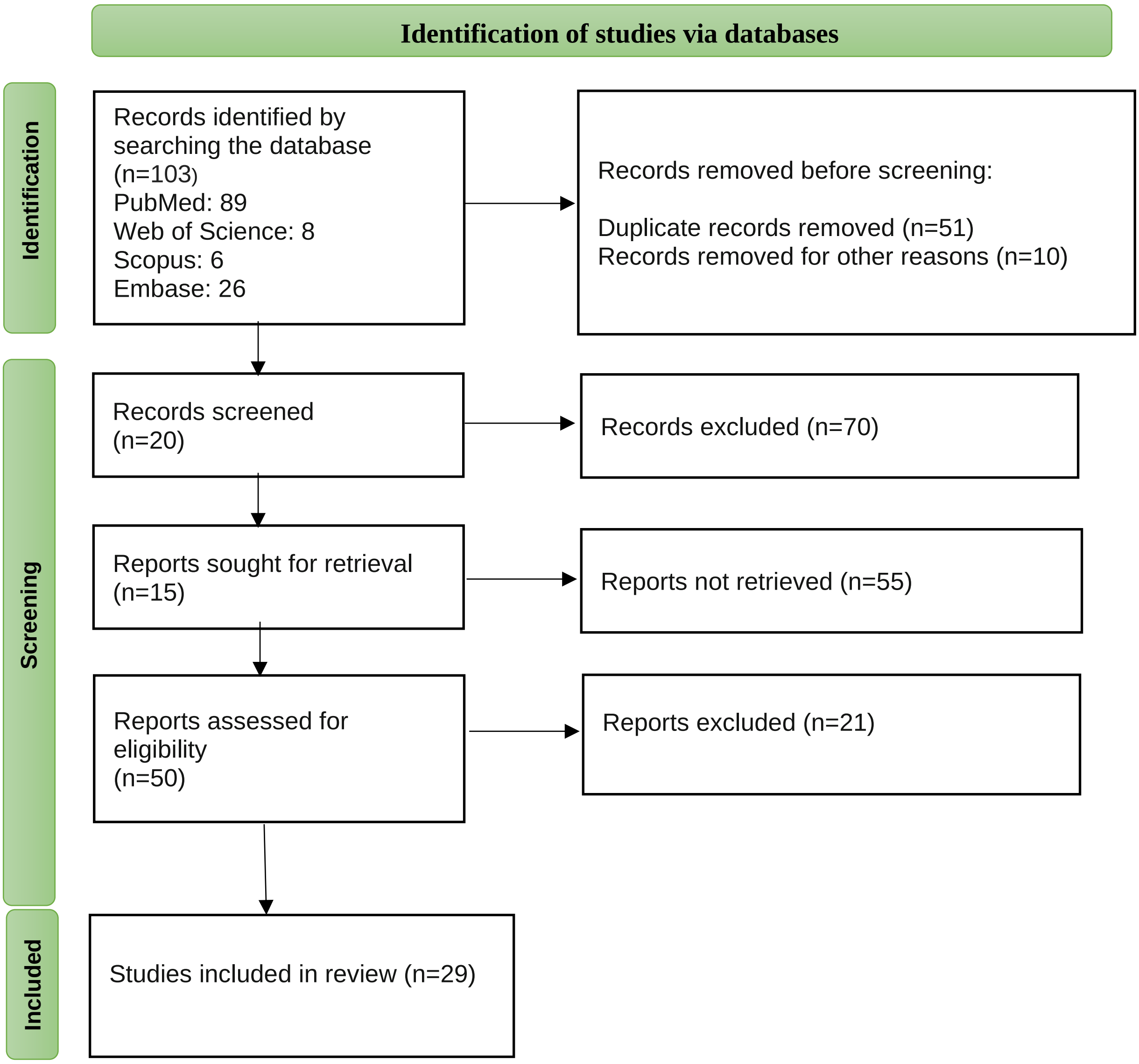

Figure 1. Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) Flow Diagram

Collectively, these results highlight the transformative potential of combining quantum computing with AI in the field of oncology. By significantly accelerating data processing speeds and improving model performance, QML could mitigate the limitations of classical machine learning, particularly in managing the vast and complex datasets associated with genomics, histopathology, and radiological imaging (Figure 4).

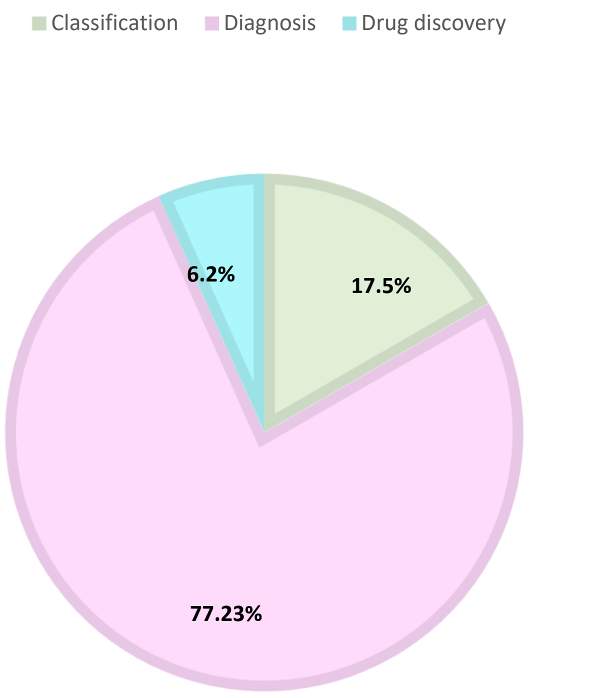

Figure 2. Use of Quantum Machine Learning in Different Areas

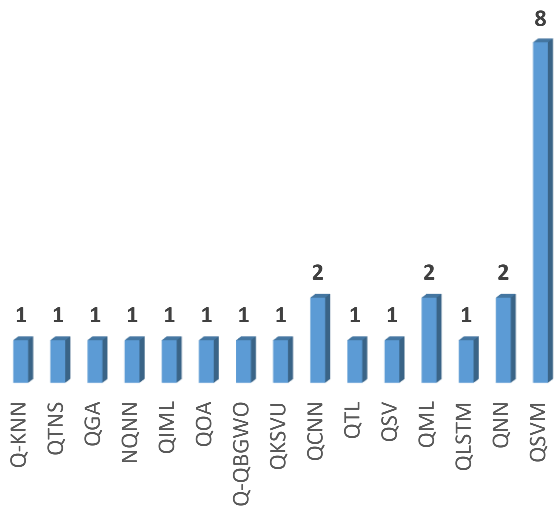

Figure 3. Quantum Machine Learning Algorithm Frequency. NQNN, noisy quantum neural network; Q-GBGWO, quantum grey wolf optimizer; Q-KNN, quantum k-nearest neighbors; QCNN, quantum convolutional neural network; QGA, quantum genetic algorithm; QiML, quantum-inspired machine learning; QKSVM, quantum kernel support vector machine; QLSTM, quantum long short-term memory; QML, quantum machine learning; QNN, quantum neural network; QOA, Quantum-Optimized AlexNet; QSVC, quantum support vector classifier; QSVM, quantum support vector machine; QTL, quantum transfer learning; QTNS, quantum tensor networks

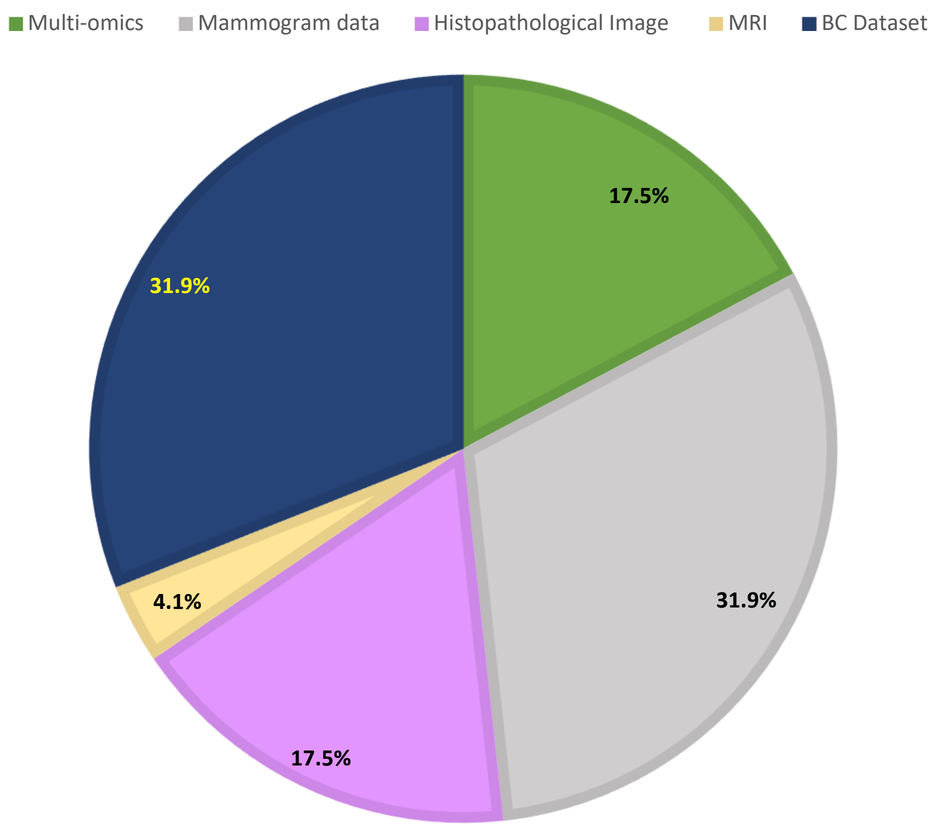

Figure 4. Quantum Machine Learning in Different Data Types

Table 2. Study summaries about QML in Breast cancer study

Names of authors, country, and year of publication	Area used	AI methods	Data set	Tools	Output
Ghoabdi *et al.* [22] 2023 Iran	Classification	QSVM, skqulacs-QSVM	GDC TCGA RNA-seq (HTSeq)	Python	Acc=100 Speed=high
Al Ali *et al.* [23] 2022 Iraq	Detection	QNN	Mammogram data	MATLAB and Python	Acc=88%
Zhang *et al.* [24] 2024 China	Drug discovery	QLSTM	Drug discovery sourced from MoleculeNet and breast cancer cell lines	PyTorch	Acc=84%
Repetto *et al.* [25] 2024 Italy	Detection	QML	METABRIC dataset (Multi-omics dataset)	Python	
Mallick *et al.* [26] 2024 India	Classification	QSVC	Histopathological Image Classification	Python	Acc=100%
Azevedo *et al.* [27] 2022 Portugal	Detection	Quantum transfer learning	Mammography Image Analysis Society (MIAS)	Python, PennyLane	Acc=84%
Pomarico *et al.* [28] 2021 Italy	Diagnosis	QSVM	Histological outcomes of 634 patients	Python	Acc=80%
Matondo-Mvula *et al.* [29] 2024 USA	Detection	QCNN	Breast MNIST	Python	Acc=77%
Li *et al.* [30] 2021 USA	Classification	QML	Genomic data from TCGA	Python	Acc=100%
Havenstein *et al.* [31] 2018 USA	Detection	QSVM	UCI ML Breast Cancer Wisconsin	Python	Acc=100%
Premanand *et al.* [32] 2023 India	Detection	QSVC	Wisconsin BC dataset	Python	Acc=97.3%
Nguyen *et al.* [33] 2024 Vietnam	Drug discovery	QNN	TCGA	Python	Acc=97.3%
Bilal *et al.* [34] 2024 Saudi Arabia	Diagnosis	QSVM	MIAS dataset	Python	Acc=100% ROC=1
Shan *et al.* [35] 2022 China	Diagnosis	QSVM	BC dataset	Python	Acc=98%
Qasim *et al.* [36] 2022 Turkey	Detection	QNN	DDSM	Python	Acc=98.5%
Vashisth *et al.* [37] 2021 India	Diagnosis	QSVM	Breast Cancer Wisconsin Database	Python	Pre=94% Recall=94% F-score=96%

RV *et al.* [38] 2024 India	Diagnosis	QKSVM	Mammography Image	Python	Acc=84%
Bilal *et al.* [39] 2024 China	Diagnosis	Q-GBGWO , ELM	MIAS dataset	Python	Acc=97%
Balamurugan *et al.* [40] 2024 India	Diagnosis	QSVM	COCO dataset, TEM dataset, S2NANOdataset	Python	Acc=98%
Ahmed *et al.* [41] 2023 Egypt	Diagnosis	Quantum-Optimized AlexNet (QOA)	Histopathology Breast Image	Python	Acc=93%
Amin *et al.* [42] 2022 USA	Diagnosis	QNN	Histopathology Breast Image	Python	Acc=99%
Wang[43] 2024 USA	Diagnosis	QSVMF	Breast cancer dataset	Python	Acc=93%
Sergioli *et al.* [44]	Diagnosis	QiML	Histopathology Breast Image	Python	Acc=99.8%
Waris *et al.* [45] 2024 Pakistan	Diagnosis	QCNN	BUSIS and DDSM datasets	Python	Acc=99 %
Thamizhselvi *et al.* [46] 2023 India	Diagnosis	NQNN	MIAS, WBCD, and DSDM	Python	Acc=99.8%
Dong *et al.* [47] 2023 China	Diagnosis	QGA-SVM	Breast cancer dataset	Python	Acc=99.8%
Chatterjee *et al.* [48] 2023 India	Diagnosis	QSVM	Wisconsin Breast Cancer dataset	Python	Acc=99.8%
Hamdi *et al.* [49] 2015 Africa	Classification	Q- KNN	Mammography Image	Python	Acc=100
Liu *et al.* [50] 2022 China	Classification	QTNs	BreakHis dataset	Python	Acc=100

Acc, accuracy; BC, breast cancer; BUSIS, breast ultrasound images; COCO, Common Objects in Context; DDSM, Digital Database for Screening Mammography; ELM, Extreme Learning Machine; GDC, Genomic Data Commons; HTSeq, High-Throughput Sequencing; METABRIC, Molecular Taxonomy of Breast Cancer International Consortium; MIAS, Mammography Image Analysis Society; ML, machine learning; MNIST, Modified National Institute of Standards and Technology; NQNN, noisy quantum neural network; Pre, Precision; QCNN, quantum convolutional neural network; QGA-SVM, quantum genetic algorithm - support vector machine; Q-GBGWO, quantum grey wolf optimizer; Q-KNN, quantum k-nearest neighbors; QKSVM, quantum kernel support vector machine; QLSTM, quantum long short-term memory; QML, quantum machine learning; QNN, quantum neural network; QOA, Quantum-Optimized AlexNet; QSVC, quantum support vector classifier; QSVM, quantum support vector machine; QTNs, quantum tensor networks; QiML, quantum-inspired machine learning; ROC, receiver operating characteristic; RNA-seq, ribonucleic acid sequencing; SVM, support vector machine; TCGA, The Cancer Genome Atlas; TEM, transmission electron microscopy; UCI, University of California, Irvine; WBCD, Wisconsin Breast Cancer Dataset

DISCUSSION

This systematic review suggests that AI methods, especially quantum algorithms, have great potential to improve the accuracy of breast cancer diagnosis. It was observed that most studies have used advanced AI techniques such as QNN and QSVM to increase the accuracy of breast cancer diagnosis. Many of these studies have been able to achieve high accuracy (over 90%) in the identification and classification of medical images. However, further research is needed to evaluate the performance of these models in real clinical settings. Also, collaboration between researchers and clinicians can help develop more effective solutions in this area. Breast cancer is a genetic disease influenced by an individual's genomic structure. Genetic data are crucial sources of information for predicting cancer progression. AI systems can analyze patients' genetic data to identify patterns related to disease progression and assist physicians in treatment decision-making. These analyses can help identify patients at high risk of disease progression and aid in developing personalized treatments. Compared to classical computing, quantum computing technology is more energy-efficient and optimized for developing advanced AI models. This means quantum computing can enhance AI advancements in areas such as deep learning, natural language processing, and computer vision with less energy consumption. QML offers significant potential for effectively analyzing biological and medical data to minimize medical errors.[8] Therefore, leveraging QML algorithms can enhance the analysis of medical data for early disease diagnosis, leading to improved patient management, cost reduction, and better treatment outcomes.[9]

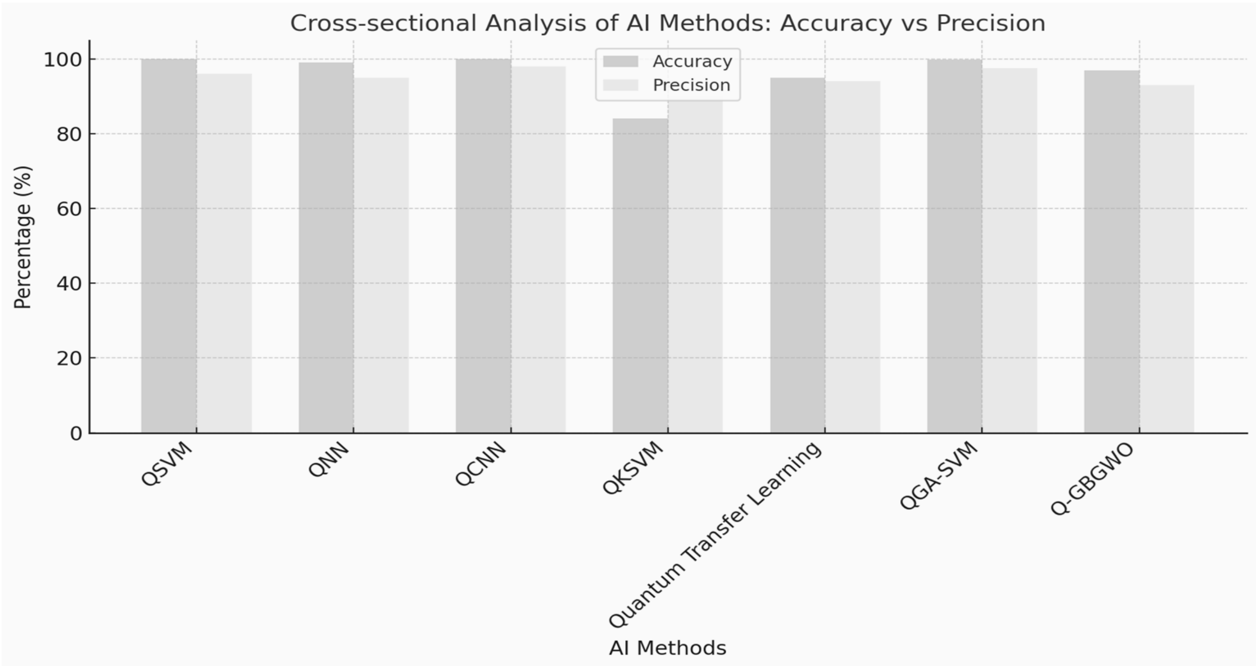

Figure 5. Cross-Sectional Artificial Intelligence Methods. Q-GBGWO, quantum grey wolf optimizer; QCNN, quantum convolutional neural network; QGA-SVM, quantum genetic algorithm - support vector machine; QKSVM, quantum kernel support vector machine; QNN, quantum neural network; QSVM, quantum support vector machine.

Based on the provided table and results, it is evident that QML techniques show great promise in enhancing breast cancer diagnosis. We reported a variety of studies employing QML algorithms like QSVM, QNN, and QCNN. These methods were applied across different data types, including genomic data, mammogram images, histopathological images, and magnetic resonance imaging (MRI) data, with a focus on classification, detection, and diagnosis of breast cancer. A significant number of these studies reported high accuracy, often exceeding 90%, and even reaching 100% in some instances, suggesting a potential advantage over classical machine learning methods. For example, Ghoabdi *et al.* achieved 100% accuracy using QSVM for classification. Similarly, studies using QCNN for detection and diagnosis have also reported accuracy scores close to 100%. The consistency of high accuracy across different QML methods and datasets suggests a strong capability for handling the complex and noisy data associated with breast cancer.

Furthermore, the comparison between QML and classical AI methods highlights QML's potential to address limitations of classical approaches. Several studies mentioned in the discussion section used classical machine learning, such as CNNs, and reported high accuracy, sensitivity, and specificity in breast cancer diagnosis. However, the research suggests that QML may offer an edge in terms of increased processing speed, reduced noise, and better feature extraction. Additionally, the use of quantum transfer learning and quantum kernel methods further improves diagnostic precision from complex imaging data. Overall, while classical methods have shown good results, the potential of QML to enhance speed, accuracy, and handle complex data points toward significant advancements in breast cancer diagnosis and personalized treatment. However, this study also acknowledges that the technology is still in early stages and requires further evaluation in clinical settings.

In addition, Charan *et al.* (2021) used CNN techniques on 342 mammographic images, resulting in an area under the receiver operating characteristic (ROC) curve of 0.879.[51] Using CNN and CoroNet techniques on 2620 images from the North Florida Digital Imaging Database to diagnose breast cancer, Mobark *et al.* (2022) reported that the accuracy achieved was 94.92% and 88.67%, respectively.[52] Meanwhile, some studies that employed QCNN techniques[29, 49] on diagnostic breast cancer images, an accuracy index of 100% was reported, indicating that QCNN can learn faster or achieve better test accuracy with fewer training sessions.

Also, Li *et al.* used a CNN on mammographic images of 394 breast cancer patients to assess the risk of breast cancer. The area under the ROC curve in this study was approximately 0.834.[30] In a study by Liu and colleagues, a CNN was used on clinical data and mammographic images to diagnose four types of microcalcifications observed in malignancies. The area under the curve, sensitivity, and specificity indices for this model were 0.910, 91.9%, and 85.3%, respectively.[50] In another study, Fathy *et al.* used a CNN on 2517 mammographic images of breast cancer patients to identify breast masses, with results showing an area under the ROC curve of 0.965 for mass detection.[53] In a study by Altan *et al.* for classifying breast cancer using CNN on mammographic images, the deep learning model achieved high accuracy, sensitivity, and specificity indices, which were 92.48%, 95.30%, and 96.72%, respectively.[54]

Additionally, Huang *et al.* designed a deep learning-based decision support system to assess breast cancer risk using CNN and text processing techniques on demographic and clinical data, along with mammographic images of 5107 breast cancer patients. The model demonstrated 100% sensitivity, 74% specificity, 81% accuracy, and an area under the curve of 0.93%.[55] Similar studies, such as the one by Mohapatra *et al.*, used VGG-16 and AlexNet techniques on 9752 mammographic films for breast cancer mass identification. The results showed an area under the curve (0.86) and an accuracy (65%) for the AlexNet model that were better than VGG-16.[56] In other similar studies, Khuriwal *et al.* conducted a study to identify breast cancer in mammographic films using CNN on 4356 films with 12 features, achieving an accuracy of 98%.[57] Duggento *et al.* performed a study using a deep neural network like CNN on the DDSM database with 12 features to identify and diagnose breast cancer, reporting an area under the curve of 0.729.[58]

Also, Malebary *et al.* utilized techniques such as RNN, CNN, VGG, RF, and BT on the public DDSM database to classify mammographic images of breast cancer. The area under the curve for ResNet and ResNet-VGG networks was reported to be 0.923 and 0.958, respectively, indicating superior capability in classifying mammographic images compared to other models.[59] In another study, Ahn *et al.* estimated breast density using CNN on 392 mammographic images, reporting a diagnostic accuracy of 96%.[60] Similarly, Chakravarthy *et al.* used deep learning techniques such as SVM with RBF kernel, ELM, and PSO on three databases (DDSM, MIAS, IN-breast) for breast cancer identification and reported PSO accuracy rates of 98.13%, 98.26%, and 97.19%, respectively, across the databases, showing superior image classification ability, compared to other models.[61]

One-way quantum features can aid machine learning through quantum superposition, allowing the machine to perform different stages of a task simultaneously and in parallel. Such a capability can significantly increase learning speed and efficiency. Although quantum machine learning has numerous advantages, research shows that in some areas, classical machine learning performs better. In this regard, Zheng *et al.* diagnosed breast cancer using Deep Learning assisted Efficient Adaboost Algorithm (DLA-EABA) and CNN techniques on mammographic, ultrasound, CT scan, and MRI images. The results from DLA-EABA showed an accuracy of 97.45%, sensitivity of 98.3%, and specificity of 96.4%, demonstrating higher capability than other models.[62]

While quantum computing holds great potential, it is still in its early stages of development and faces many technical challenges. These challenges include qubit stability, quantum errors, and the need for extremely cold environments for quantum systems to function. As research progresses in both fields, the interaction between quantum computing and AI is expected to yield significant results, transforming industries such as medicine, finance, logistics, and information technology. Although evaluating the overall performance of quantum models on a large scale is difficult due to the limited size of quantum circuits, we can be hopeful that it might be reliably achievable in the near future.

Limitations and Suggestions

Quantum computing is still in its early stages, facing technical hurdles like qubit stability and quantum errors, and requiring extremely cold

environments to function. This makes it challenging to implement and evaluate QML models on a large scale. The limited size of quantum circuits makes it difficult to evaluate the overall performance of quantum models on a large scale. This makes it difficult to draw definitive conclusions about their effectiveness. Although many studies have achieved high accuracy using QML, further research is needed to evaluate these models in real clinical settings.
Instead of just lab-based experiments, future studies should focus on integrating QML models directly into clinical workflows. This means testing models in real hospitals with diverse patient populations, not just in controlled environments. This would help assess the practicality and real-world effectiveness of QML in improving breast cancer diagnosis and treatment. Rather than focusing on small-scale quantum circuits, future research should aim to scale up quantum technology to evaluate model performance on larger datasets. This is crucial to assess the reliability of QML in handling complex medical data. Future research should aim to develop more stable and error-resistant quantum systems. This means researching new ways to correct quantum errors and make quantum computers more reliable and resilient for practical applications. Future studies should promote interdisciplinary research and encourage collaboration among quantum computing experts, AI researchers, and clinical practitioners. This will ensure that research is driven by real clinical needs. Rather than sticking to standard quantum algorithms, future research should look to develop novel QML algorithms tailored to specific breast cancer data challenges. This could lead to algorithms that can analyze genomic, histopathological, and radiological data more efficiently. This will help to reveal the unique advantages and disadvantages of each approach and understand which one is best suited for particular tasks. Researchers should focus on using QML to develop personalized treatment strategies based on an individual's genetic makeup, medical history, and other factors. This could involve analyzing complex genomic and multi-omics data with quantum techniques to identify precise biomarkers for early detection and targeted treatments. Future research should develop novel methods for managing and analyzing large, multidimensional breast cancer datasets. This would allow for the discovery of patterns that could improve diagnosis, treatment, and prognosis. In summary, while QML holds great potential for transforming breast cancer diagnosis and treatment, significant limitations need to be addressed in future research. This includes not only improving the technical aspects of quantum computing but also focusing on real-world clinical applications, interdisciplinary collaboration, and novel algorithm development.

CONCLUSION

The presence of various signs and features of breast cancer makes it challenging for physicians to diagnose; hence, accurate prediction of this disease is crucial. Breast cancer data is highly complex due to diverse biological characteristics, the abundance of genomic and proteomic patterns, and clinical factors such as patient age, treatment history, and impactful environmental risk factors.

By collecting more precise information, such as gene expression profiles, histopathological images, and treatment responses. The challenge lies in managing and analyzing these large and multidimensional datasets to identify patterns that could improve diagnosis, treatment, and prognosis. Due to the ability of quantum computers to process and represent high-dimensional spaces more efficiently than classical computers, QML offers potential advantages for handling such complex data. QML algorithms, such as QSVM or quantum principal component analysis (QPCA), can identify the most significant features of genomic or imaging data more quickly than classical methods and enhance predictive models.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest. No institution has financially supported this research, and the authors have provided all the necessary financial resources.

ETHICAL CONSIDERATIONS

Not applicable.

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DATA AVAILABILITY

Data related to this study are presented in the article.

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