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Oncological Applications of Quantum Machine Learning

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Abstract

Background: Cancer is a leading cause of death worldwide. Machine learning (ML) and quantum computers (QCs) have recently advanced significantly. Numerous studies have examined the application of quantum machine learning (QML) in healthcare and validated its superiority over classical ML algorithms. **Objectives:** This review investigates and reports the oncological applications of QML. **Methods:** In March 2023, an electronic investigation of PubMed, Scopus, Web of Science, IEEE, and Cochrane databases was performed. The articles were screened based on titles and abstracts, and their full texts were examined. **Results:** Initially, a total of 207 articles were retrieved. Thereafter, 9 articles were included in the study, most of which were published from 2020 onwards. The results indicated the implementation of various QML techniques in different aspects of oncology, such as reducing mammography image noise, edge detection of breast cancer, clinical decision support in radiotherapy treatment, and cancer classification. **Conclusion:** These studies revealed that integrating quantum science with ML can significantly improve patient care and clinical outcomes. Future studies should explore the integration of QC and ML and the development of novel algorithms to enhance cancer prognosis, diagnosis, and treatment planning.

Keywords

machine learning, quantum computer, quantum machine learning, cancer, oncology

Abbreviations

ML, machine learning; DL, deep learning; AL, artificial intelligence; QC, quantum computer; QML, quantum machine learning; QRL, quantum reinforcement learning; QSVM, quantum support vector machines; QNM, quantum neural networks; QS, quantum simulators; QBM, quantum Boltzmann machines; APCNN, atrous pyramid convolutional neural network; QICO, quantum-inspired immune clone optimization; CNN, convolutional neural networks; QTL, quantum transfer learning; QDRL, quantum deep reinforcement learning; AWS, Amazon web services; NV, Nitrogen-vacancy; PSNR, peak signal-to-noise ratio; MSE, mean squared error.

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Introduction

Cancer, a leading cause of global deaths, is a group of diseases caused by uncontrolled growth and spread of abnormal cells.[1] In developed and developing countries, cancer cases have been increasing gradually, the most common types being breast, lung, colon, rectal, and prostate cancers.[2] Nearly one-third of cancer deaths are attributed to smoking, BMI, alcohol consumption, inadequate consumption of fruits and vegetables, and lack of physical activity.[2,3] Cancer-causing infections, such as HPV and hepatitis, account for approximately 30% of cases in low- and middle-income countries.[3] In 2020, approximately 19.3 million new cases and 10 million cancer-related deaths were reported, and these figures are expected to increase in the next few decades.[1,3–4] Over the past decades, cancer treatment options have expanded; however, only a few patients can access and afford these options. Therefore, enhancing the affordability and personalization of cancer treatment is

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necessary.[5] Early cancer detection increases the possibility of treatment and recovery.[3] As a complex disease, the development and growth of cancer involve numerous microscopic and macroscopic changes in cell morphology that remain to be completely understood.[5] Recently, machine learning (ML) techniques, such as deep neural networks, have attracted attention to assist cancer diagnosis and treatment.[6,7]

Artificial intelligence (AI), a branch of computer science, has advanced significantly in various fields, including healthcare, medicine, and biomedical research.[8,9] AI enables computers with decision-making and logical reasoning to solve complex and novel problems.[7] Furthermore, deep learning (DL) is a ubiquitous and widely used sub-discipline of ML. Its infrastructure is a powerful framework leveraging transformation and graph technologies to construct complex multilayered learning models. In ML algorithms, the data quality is directly related to the degree of learning and generalization of the models. Thus, most studies have implemented feature engineering and extraction methods.[8,9] DL has been used to simulate the human brain processes for designing models that can extract essential features from raw and cleaned data.[10,11] Deep convolutional networks with a multilayer architecture have been designed to extract low-level features in the initial layers, whereas higher-level features are extracted in the subsequent layers as the model is fed with data.[11] This field has wide applications in various scientific and technical areas, such as data mining, medical diagnosis, computer vision, and natural language processing.[7,12]

Generally, ML uses linear algebra for data processing using matrix data as the input.[9] Advancements in these technologies have rendered classical computing limited, owing to its architecture of bits and classical algorithms. However, quantum computing potentially overcomes these limitations using quantum bits or qubits.[13] It is a novel field that combines computer science, mathematics, and physics to build quantum computers (QCs).[14] Contrary to bits, qubits can possess values of 0, 1, or a superposition of both, thus enabling the parallel-processing of massive matrix data.[13,14] Quantum computing is based on the principles of quantum physics, which governs the behavior of matter at the molecular and subatomic levels, and propounds that particles can exhibit wave- and particle-like characteristics.[15]

Compared to classical computers, QCs can perform certain calculations exponentially faster because they can simultaneously exist in multiple states through superposition, which is accomplished using quantum parallelism.[13] Using QCs, the performance of routine tasks is seldom faster or slower than that using conventional computing. However, the time period that classical computers require to solve specific problems remains to be determined. QCs can solve similar problems rapidly and with less storage space by employing specific quantum algorithms. However, this does not imply that all tasks must be transferred to QCs.

Quantum computing has various applications in cryptography, healthcare, and AI.[15] Applying ML algorithms based on the principles of quantum computing has created a new field called quantum machine learning (QML),[16] which has significantly advanced classical ML applications (Figure 1). Furthermore, QCs may solve problems beyond the capabilities of the most powerful classical supercomputers.[17] For instance, Grover & Shor's algorithms have demonstrated quadratic and exponential speed-up in exploring unstructured databases and solving integer factorization problems.[16,18]

To enhance the speed and efficiency of ML relative to its classical computer counterparts, QML examines the designing and implementation of quantum software.[19] QML uses quantum algorithms as part of its implementation, potentially outperforming classical ML algorithms for specific problems.[17,19] Various QML algorithms have been proposed, such as quantum reinforcement learning (QRL), quantum principal component analysis, quantum support vector machines (QSVM), and quantum neural networks (QNN).[20] Particularly, QRL performs excellently in quantum simulators (QS). In a QRL algorithm, a quantum agent interacts with the environment and receives rewards for its actions, and the model maximizes the number of rewards received.[21] Theoretically, QRL may achieve exponential performance speed-up compared to its classical counterpart.[21]

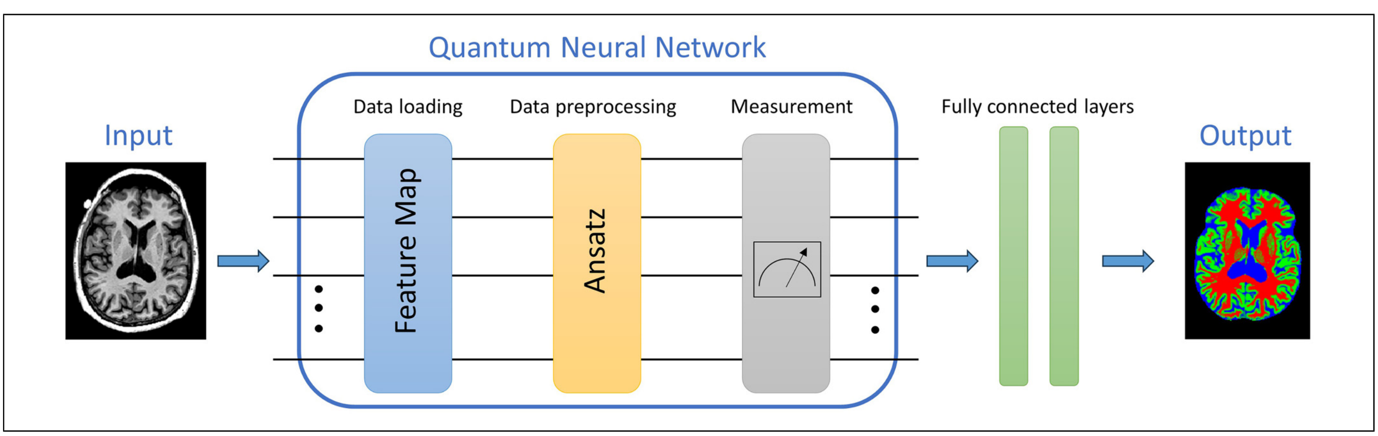

Figure 1. Hybrid quantum convolutional neural networks architecture.

Quantum approximate optimization algorithm and quantum gradient descent are 2 renowned examples of quantum enhanced optimization algorithms used in QNNs, such as quantum Boltzmann machines (QBM).[16] Quantum computing can advantageously harness the power of quantum entanglement, quantum superposition, and quantum coherence. These fundamental quantum phenomena pave the way for a novel information processing approach, potentially outperforming classical DL models.[16,20]

AI has advanced significantly to mitigate the increasing prevalence of cancer and facilitate its prevention and early detection. Combining quantum computing with AI can herald a new era in data processing and digitization. This study provides a fundamental overview of the oncological applications of QML in healthcare. As a burgeoning interdisciplinary field, it is the first to catalog and synthesize scientific developments systematically.

Methods

This study employed a systematic search strategy designed based on previous studies and the criteria established by authors. We considered all articles that used quantum computing and ML in oncology. In March 2023, an electronic search was performed to obtain these articles using 5 search engines, that is, PubMed, Scopus, ISI Web of Sciences, IEEE, and Cochrane, without a time filter. A combination of terms, including "quantum," "deep learning," "machine learning," "oncology," and "cancer" was used to build the search strategy. The format of this search is as follows: ("Oncology") AND ("Deep learning" OR "Machine learning") AND ("Oncology" OR "Cancer").

The inclusion and exclusion criteria for the selected articles were carefully defined. For inclusion, the article must satisfy the following conditions: (i) Investigating the oncological applications of quantum computing and ML, which includes articles concerning QCs and QSs, and those based on algorithms inspired by quantum physics. (ii) The articles should be written in English. For the review, we considered complete articles with full content available, complying with the aforementioned criteria.

Articles were excluded from the review if they satisfied at least 1 of the following criteria: (i) pertaining to diseases other than cancer; (ii) published in languages other than English; (iii) conference papers; (iv) focused solely on Quantum Computing or ML without considering their applications; and (v) classified as review articles, meta-analyses, letters to the editor, or books. Figure 2 shows the preferred reporting items for systematic reviews and meta-analyses (PRISMA) flow diagram visualizing the selection of articles for review.

Data Collection

The data extraction procedure followed a predetermined template. The assembled dataset included various informative elements, such as the title of the article, authorship, journal source, country of origin, year of publication, important data attributes, the particular type of cancer under consideration, and insights into the use of QML algorithms. Additionally, important facets of the articles are noted, including their primary goals, theoretical frameworks, findings, remarks, and limitations. This thorough data extraction procedure simplified performing a structured analysis of the reviewed articles. Data collection was performed independently by the first author, and in case of discrepancies, the corresponding author was consulted. The extracted data elements are summarized in Tables 1 and 2.

Results

After performing an initial search in the 4 databases, 258 articles were identified. This study included 9 articles after screening the titles and abstracts and examining the methods and findings (Figure 2). For analytical clarity, the included studies were divided into 2 groups. As shown in Table 1, the first group, which consists of 5 entries, includes articles that utilized QML methodologies for predictive modeling. As shown in Table 2, the second group, which consists of 4 entries, focuses on articles that attempt to develop or implement various QML algorithms. This division simplifies the organization of the articles' goals and content for their presentation and discussion.

The analysis of the collected data indicated that most articles were published in the last 2 years (2021 and 2022). Considering that a time filter was not included in the systematic search, these results indicate the nascency of this field of study. Additionally, the frequency of articles based on country of origin was examined. Research teams from the United Arab Emirates, the United States of America, and India published the most significant articles.

The included articles primarily focused on breast cancer (5 articles),[22–26] lung cancer (2 articles),[27,28] and prostate cancer (1 article).[29] The datasets included imaging, genomic, or clinical data. Image and genomic datasets were used the most, containing 5[23–26,29] and 3[27,28,30] articles, respectively. All articles focused on breast cancer used image data to feed the model. Imaging data for breast cancer included medical mammography, ultrasound, and microscopic whole-slide imaging (WSI). Two articles[27,28] on lung cancer used genomic, biological, and clinical data. An article[29] on prostate cancer benefited from WSI microscopic imaging. To implement algorithms in medical image processing, the prevalent approaches include noise reduction, filtering, edge detection, and mass detection of cancerous tumors.

The objectives of the articles listed in Table 1 are cancer diagnosis, identification, and screening. The 3 articles in Table 1[23,27,28] used Qiskit and PennyLane QSs, benefiting from IBM and D-Wave QCs. Additionally, the quantum physics theory was used to improve QML algorithms. Among the 4 articles listed in Table 2, 1[25] described a method for noise reduction and accurate mass segmentation in mammography images using a wavelet transform filter and morphological image operations based on the atrous pyramid convolutional

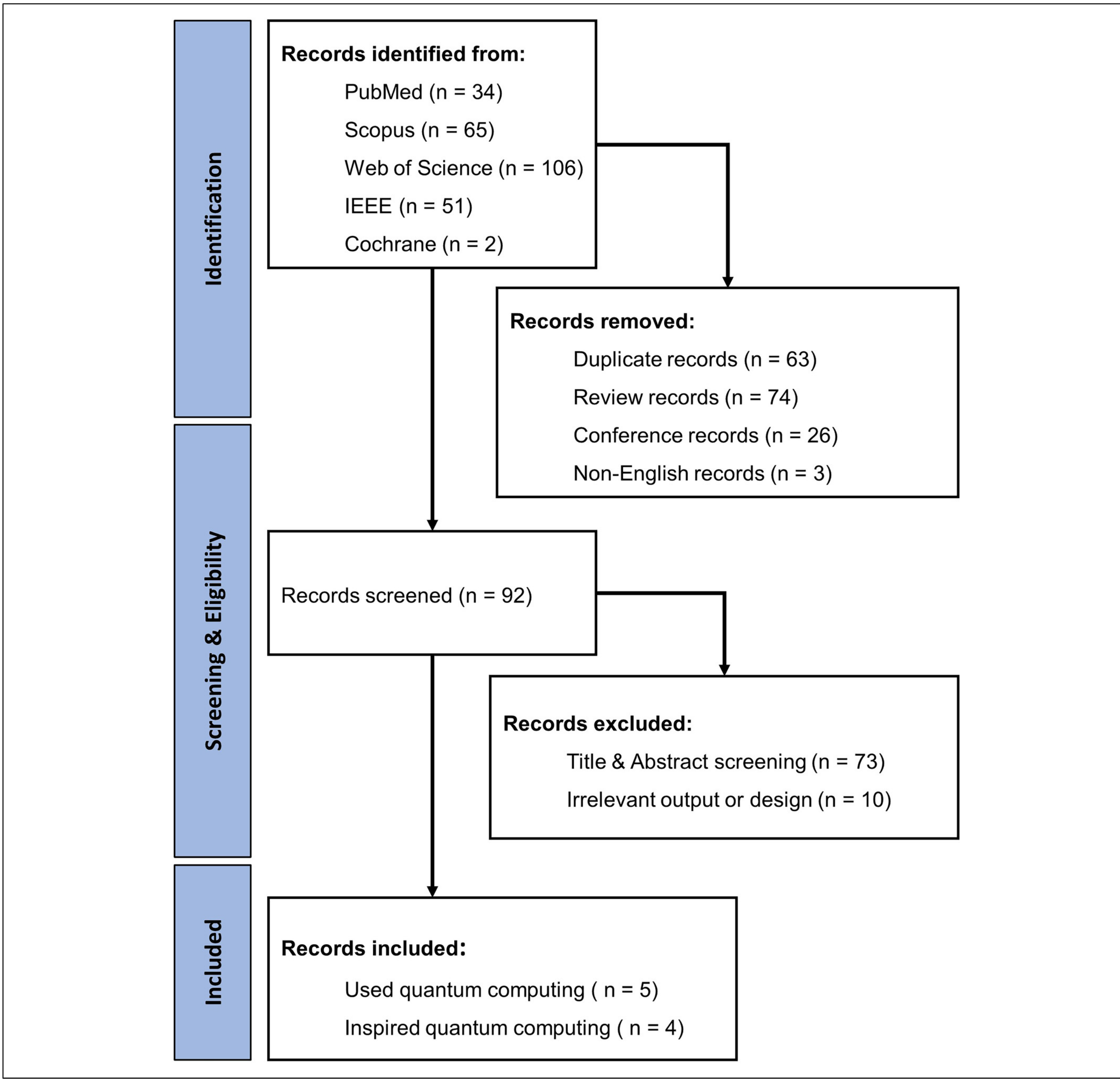

Figure 2. Flow diagram of the identification and selection process following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines.

neural network (APCNN) DL model. Another article[26] employed the quantum genetic algorithm to solve the multilevel threshold problem. In 1 article,[31] the quantum-inspired immune clone optimization (QICO) algorithm based on the quantum computing theory was used to select the optimal feature for classifying cancer data. Furthermore, the quantum physics-based quantum measurement regression (QMR) algorithm[30] was used to improve the interpretability of results, and the entered articles were analyzed separately (Table 3).

Several studies have proposed novel methods for image processing (segmentation and classification) and optimization by introducing techniques, such as quantum wavelet transform filters,[25] quantum genetic algorithms,[26] QICO,[28] and deep quantum ordinal regressions.[30] These methods combine classical ML algorithms, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), with techniques inspired by quantum physics to improve performance.

A hybrid quantum-classical approach was used in 3 articles[23,24,27] on cancer screening and classification. Utilizing the classical and QC resources, this approach offers better robustness and scalability than the classical or quantum methods. These studies combined the computational

Table 1. The Characteristics of the Included Articles That Implemented Quantum Computing.

First author	Journal	Year	Country	Data	Cancer	Quantum computing
Dipesh Niraula[27]	Scientific Reports	2021	USA	Biological, physical, genetic, clinical, and dosimetric factors data	Lung	Qiskit quantum simulator. IBM quantum computer.
Siddhant Jain[28]	SN Applied Sciences	2020	Canada	Gene expression data	Lung	D-Wave quantum computer device.
Shubham Vashisth[22]	Journal of Intelligent Systems	2021	India	Clinical	Breast	Qiskit quantum simulator.
Vanda Azevedo[23]	Quantum Machine Intelligence	2022	Portugal	Mammogram images	Breast	IBM quantum-computing device.
Javaria Amin[24]	Microscopy Research and Technique	2022	Pakistan, USA, UK, Saudi Arabia	Ultrasound, WSI images	Breast	PennyLane quantum machine learning library.

Table 2. The Characteristics of the Included Articles Influenced by Quantum Physics.

First author	Journal	Year	Country	Data	Cancer	Inspired by quantum physics
Mohammed N. Qasim[25]	Scientific Programming	2022	Turkey, Iraq	Mammographic images	Breast	Quantum wavelet transform
Amani Tariq Jamal[26]	Neural Computing and Applications	2021	Saudi Arabia	Mammographic images	Breast	Quantum genetic algorithm
Nageswara Rao Eluri[30]	Data Technologies and Applications	2021	India	Gene expression data	-	Quantum-inspired Immune Clone Optimization Algorithm
Santiago Toledo-Cortes[29]	Computers in Biology and Medicine	2022	Colombia, Switzerland	WSI image	Prostate	Quantum measurement regression

advantages of QC with classical algorithms to increase the overall performance and efficiency.

Other studies focused on developing quantum-based frameworks for clinical decision support, such as the quantum deep reinforcement learning (QDRL) framework for radiation therapy[27] and quantum SVM classification algorithms.[22]

The proposed methods demonstrate improved performance in various areas of oncology. For instance, 1 article[27] exhibited noise reduction and better mass detection accuracy than previous methods, whereas 2 articles[22,25] demonstrated increased edge detection performance and classification accuracy, respectively. Two articles presented the potential of quantum-based frameworks to improve radiotherapy decision-making and the classification of non-small cell lung cancer subtypes.[22,23]

Article[31] demonstrates that the QICO-based feature selection model outperforms other discovery-based models, and the optimized RNN achieves better results than other ML methods.

The DQOR model[29] was evaluated for prostate cancer diagnosis and diabetic retinopathy grade assessment, exhibiting improved diagnostic performance compared to DL-based models. Article[24] compares various SVM classification algorithms for breast cancer detection and highlights the superior performances of quantum SVMs. Finally, article[26] used pretrained Xception and Deeplabv3 models to propose a hybrid semantic model for breast cancer classification and malignancy detection, achieving remarkable accuracy (95% accuracy for classification and 99% for diagnosis).

Compared to the traditional methods, these articles combined the classical ML methods with quantum-physics-inspired techniques to improve performance metrics, such as accuracy, precision, recall, and F1-score.

Discussion

Technology-driven innovation refers to shifts in the combined working of new and old technological operations and their acceptance and adaptation in a market.[32] In the post-digital era,[33] the convergence of Industry 4.0 technologies will give rise to new applications. Industry 4.0 is expected to undergo a revolution due to quantum technology, which relies on probabilities instead of binary bits and promises significant innovation.[34] A few companies, such as IBM, Google, IonQ, and Honeywell, are prepared to provide cloud services for commercial access to quantum technology via Microsoft or Amazon web services (AWS)-based infrastructures. QCs are not expected to replace personal computers in the near future. However, startups leveraging cloud-based quantum-computing services to address important issues, particularly in healthcare, have emerged.[34]

A QC is a physical device using the principles of quantum physics to perform computational tasks. However, these devices are still in the primitive stages of development and are widely unavailable. Currently, quantum devices have distinct hardware, which includes superconductors, trapped ions, topological qubits, photons, nitrogen-vacancy (NV) centers,

Table 3. The 5 Key Sections of The Included Articles.

Ref	Objective	Method	Results	Conclusion	Limitations
25	To propose an optimal approach for reducing noise in mammographic images and identifying different types of noise to improve mass detection accuracy.	Combining quantum wavelet transform filtering with an APCNN for noise reduction, morphological image operations, and mass segmentation for classification.	The proposed approach outperforms previous methods in terms of noise reduction and mass detection accuracy, with an accuracy of 98.57%, sensitivity of 90%, specificity of 85%, and ROC and AUC with a rate of 86.77.	The proposed approach exhibits superior noise reduction and segmentation performance compared to state-of-the-art methods.	The proposed method was evaluated only on the MIAS dataset, and further evaluation on other datasets is required to validate its effectiveness.
26	To propose novel approaches for breast cancer edge detection in mammographic images.	Using a quantum genetic algorithm and support vector machines for edge detection, and comparing the results with those of standard methods.	The proposed methods exhibited improved detection of breast cancer edges in mammographic images.	ML techniques and evolutionary algorithms can be further explored for edge detection and image processing in biomedical imaging.	The proposed methods were evaluated on a limited sample of mammographic images and may not be generalized to other datasets.
27	To develop a QDRL framework for clinical decision support in radiotherapy treatment.	Using indeterministic quantum states to represent human decision-making and pairing quantum decision states with a model-based deep q-learning algorithm to optimize the clinical decision-making process in radiotherapy.	Compared to unaided clinical practice, the proposed framework can potentially improve clinical radiotherapy decision-making by at least 10%.	The proposed framework can estimate a patient's dose-response mid-treatment and recommend an optimal dose adjustment, considering individual patient information.	The proposed framework requires further validation in a prospective study to provide a necessary framework and improve the standard of care in personalized radiotherapy.
28	Classifying 2 non-small cell lung cancer subtypes using classical and quantum ML models.	Feature selection methods and a novel data representation method QCrush were used, and ML was performed using a QBM.	Successfully classified patients with adenocarcinoma or squamous cell carcinoma with high accuracy.	The study demonstrates the potential of QML in precision medicine for personalized cancer treatments.	Quantum supremacy was not demonstrated, and the sample size was relatively small, with only 104 patients.
30	To develop a cancer data classification model using gene expression data.	The proposed model involves feature extraction, optimal feature selection using the QICO algorithm, and classification using RNN.	The experimental analysis shows that the proposed QICO-RNN model outperforms other ML methods in accuracy.	The QICO algorithm effectively selects relevant features for cancer data classification using gene expression data using a suitable RNN model.	The proposed model must be tested on more datasets to evaluate its generalizability.
29	To develop a quantum-inspired deep probabilistic learning ordinal regression model for medical image diagnosis.	Combining a CNN with a differentiable probabilistic regression model called QMR to create a diagnostic support tool.	The proposed method improves the diagnosis performance and interpretability of the results on 2 different medical image analysis tasks: prostate cancer diagnosis and diabetic retinopathy grade estimation on eye fundus images.	The DQOR model outperforms state-of-the-art deep learning-based models and various closely related classification and regression methods.	The proposed method requires a large amount of labeled data for training, which may not always be available in medical image analysis tasks.
22	To implement and evaluate the performance of a QSVM classification	Using the Qiskit library, the QSVM algorithm was simulated and compared with classical	The QSVM algorithm exhibited an exponential speed-up over classical SVM	The QSVM algorithm is promising for solving classification problems and outperforms	The study was limited to a binary classification problem of breast

(continued)

Table 3. (continued)

Ref	Objective	Method	Results	Conclusion	Limitations
	algorithm for breast cancer diagnosis.	SVM algorithms on various evaluation metrics.	algorithms and achieved high accuracy in breast cancer diagnosis.	classical SVM algorithms.	cancer diagnosis and did not consider other classification problems.
23	To explore a quantum approach to ML for breast cancer screening using mammogram images.	Using a hybrid classical-quantum neural network approach to train the model using transfer learning and evaluating the performance of different architectures.	The hybrid classical-quantum neural network approach using transfer learning outperformed classical residual neural networks in classifying mammograms as malignant or benign, with an accuracy of 84%.	The hybrid classical-quantum neural network approach using transfer learning may benefit the generalization of complex data, such as mammogram images; however further testing is required.	The experiments were conducted on a relatively small dataset, and further testing on larger datasets is required to determine the generalizability of results.
24	To propose a hybrid semantic model for breast microscopic cancer classification and detection of breast malignancy using pretrained Xception and Deeplabv3 models, and a 4-qubit quantum circuit.	The proposed model is trained on input images with ground masks and transferred to a 4-qubit quantum circuit with a 6-layered architecture.	The proposed method achieved an accuracy of 95% for breast microscopic cancer classification and 99% accuracy for detecting breast malignancy.	The proposed method can relieve the pathologist's workload and subjectively mitigate the diagnosis, leading to a speedy diagnosis and increased patient survival rates.	The proposed method's performance is evaluated on publicly available benchmark datasets, and further research is required to design a standalone system for detecting breast anomalies.

and neutral atoms.[35] Contrastingly, a QS is a software program simulating the behavior of QC on a classical computer. Simulators can be used to test and develop quantum algorithms, study the behavior of QC, and explore the quantum-computing capabilities of QCs.[35] Qiskit[36] & PennyLane[37] emulators were used in 3 of the included articles.

Hybrid quantum-classical computing is a computing paradigm combining the strengths of quantum and classical computing to solve complex problems.[38] However, quantum computing is currently limited in the number and quality of qubits, rendering it difficult to perform large-scale calculations. Thus, classical computers complement QC by completing parts of the calculations that are more suitable for classical algorithms. According to 1 article,[23] some studies performed hyperparameter tuning and model training on simulators, ultimately using QCs to test the created model, owing to the limitations in the number of QC cloud devices and qubits.

The QSVM algorithm[22] is a quantum version of the linear classifier SVM. However, the QBM algorithm[28] is a quantum version of a neural network (Boltzmann machine) based on the probabilistic method of Gibbs sampling for learning. Compared to classical SVM, QSVM facilitates an exponential speed-up but is limited to linear classification. QBM can represent complex and nonlinear relationships; however, it is difficult to train and currently limited to small datasets.

Image processing for circuit-based quantum models has witnessed exciting developments, such as dimension reduction, feature extraction, and image edge extraction.[23] The approach proposed byQasim et al[25] is based on the findings of Mari et al,[39] wherein a quantum method was used to assist breast cancer screening. Mammography images were classified using the quantum transfer learning (QTL) method, which is advantageous in reducing training time, improving performance, enhancing generalization, and the possibility of accessing the latest pretrained models. Furthermore, QTL is applicable in diagnosing COVID-19 and breast cancer using medical images (CT, mammography, and ultrasound).[40]

The study[27] indicated minor differences between QDRL models using simulators and those using IBMQ, which can be attributed to 2 factors. First, the simulator lacks machine errors, including quantum decoherence errors, which introduce higher noise representative of human decision-making processes. Second, the decision selection mechanism in QDRL + simulator models differs from that in QDRL + IBMQ quantum models owing to the physical limitations of the quantum circuit design, which is shorter than the coherence length of a quantum processor.

QWT-APCNN, a hybrid of quantum wavelet transform filtering and APCNN, was assessed against existing techniques using metrics, such as the peak signal-to-noise ratio, mean-squared error, and accuracy of detection for mass area recognition. Compared with state-of-the-art techniques, the proposed method performs better at segmenting and reducing noise.[25]

Based on quantum physics, another article[29] used a QMR to increase the interpretability of an ML model. Interpretability and explainability are critical aspects of any ML model because they aid in comprehending the model's decision-making process and entrusting its predictions. These 2 factors are essential for applying ML in healthcare. Compared to QML models, the classical ML models have better interpretation and explanation capabilities. However, QML is nascent and expected to improve with its development.[41]

QML faces challenges related to software and hardware.[42] To take advantage of quantum algorithms, the hardware must be practical. Incorporating interface components, such as qRAM, is crucial to transform the classical data into a quantum mechanical form.[43] Quantum algorithms are limited to the following main issues: input, output, cost, and benchmarking.[42]

QML can handle various data modalities. Traditional ML techniques face challenges in processing and integrating large and diverse datasets, such as those from genomics, epigenomics, transcriptomics, and imaging data.[43] However, owing to their innate superposition and entanglement properties, QCs may process enormous amounts of information concurrently. Therefore, combining and analyzing various data sources in novel ways may be possible, thereby improving prediction accuracy and precision.[43] The accuracy of patient outcome predictions can be enhanced by analyzing large and matched datasets and developing state-of-the-art sample processing technologies.

The research[44] highlights the possibility that QNNs may outperform their classical counterparts in terms of training speed and data classification accuracy. These instances demonstrate the transformative potential of quantum computing in data processing and analysis, highlighting the significance of its incorporation in medical research. Despite their inherent uncertainties, this study emphasizes the growing viability of implementing QCs to advance medical sciences. Therefore, superior analytical tools may be developed to address challenging medical problems.[45]

Conclusion

The aforementioned studies demonstrate the vast potential of QML in oncology, as validated by the findings of this study. Using QML techniques, significant advancements have been made in cancer diagnosis and treatment planning. Future research should explore the integration of quantum computing and ML and the development of novel algorithms and frameworks. Owing to the developments in quantum computing, the oncological application of QML may advance patient care and clinical results. Furthermore, it is preferable to establish the rules for implementing QML algorithms in healthcare. Utilizing the power of quantum computing and ML may realize the full potential of personalized cancer care.

However, research opportunities for QML algorithms are virtually limited. Large quantities of quantum bits and data will aid the improvement and advancement of quantum technology. Hence, various data-encoding techniques should be investigated for applying QML to human healthcare issues.

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