RESEARCH PAPER

Variational Quantum Convolutional Neural Networks for Multi-Class Medical Image Classification

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Abstract
Medical image classification is an important component in computer-aided diagnosis and currently popular deep learning models are found to be inefficient in capturing the complex spatial relationships between the medical images while performing efficiently and generalizing well for multi-class classification. In this work, we introduce a novel Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) based on quantum feature encoding and adaptive variational quantum convolution, multi-scale entanglement fusion, hybrid quantum–classical optimization, and uncertainty-aware prediction to boost the diagnostic accuracy. It has been successfully applied to PennyLane and TensorFlow, and evaluated using the MedMNIST v2 multi-class medical imaging benchmark with standard metrics.Implements and tests this framework with PennyLane and TensorFlow and uses MedMNIST v2 benchmark for medical imaging with standard performance metrics. Through experiments, an accuracy of 98.21%,precision of 97.94%,recall of 97.73%,F1 score of 97.83% and an AUC of 0.996 were achieved with training time of only 82 minutes, inference time of 9.4ms/image, 6.3 million parameters and 5.4GB of GPU memory. The results demonstrate its potential to provide a scalable and reliable quantum-enhanced framework for next-generation intelligent clinical decision support system, with its ability to boost both the classification accuracy and computation efficiency.
Keywords: Variational Quantum Convolutional Neural Network, Quantum Machine Learning, Medical Image Classification, Hybrid Quantum-Classical Learning, Multi-Class Classification, Quantum Artificial Intelligence
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1. Introduction

Image classification is an important technique for medical field and it has been playing a vital role in image diagnosis based on image acquired through MRI, computed tomography (CT), X-ray, ultrasound, and histopathology images of various diseases[1]. With the explosive growth of medical imaging data, there is a growing demand for intelligent computer-aided diagnostic systems with the ability to make accurate, reliable and timely clinical decisions[2]. Classifying images is a demanding task that has recently been achieved with significant success using deep-learning techniques, in particular with convolutional neural networks (CNNs) which automatically extract the image features in a hierarchical manner. The traditional CNNs, however, require huge amounts of annotated data, high computation resources and also long training time, while the ability of generalization in heterogeneous clinical conditions is low[3,4].

Quantum Computing has recently garnered significant interest and quantum machine learning (QML) is a new paradigm for tackling some challenging optimization and pattern recognition tasks[5]. The hybrid quantum-classical learning architectures combine the representational power of quantum circuits with the optimization power of classical neural networks: quantum superposition and entanglement offer richer representations of features, while variational parameters of quantum circuits offer optimization power[6]. As a result, quantum enhanced convolutional neural networks, variational quantum classifiers and hybrid quantum convolutional architectures have shown promising results in various medical image classification tasks such as classification of brain tumors, skin diseases, and cancer[7].

But the existing quantum learning models remain constrained by the existing qubit architecture, implementation of a particular disease, small benchmark data sets, and lack of fault-tolerant in noisy quantum settings. The current literature concentrates on the classification accuracy while not addressing the adaptive quantum features extraction, multi-scale feature fusion, uncertainty-aware prediction and efficiency of computational processes under a single framework. In addition, scalable hybrid optimization techniques that can be adapted to allow for robust classification of medical images of multiple classes on multi-modal medical images are poorly investigated. The challenges are all daunting and make it difficult to implement a quantum learning system in the real clinical context.

The limitations are overcome by introducing this work with Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) for multi-class classification of medical images. The framework that is proposed integrates these features to improve the diagnostic accuracy and computational efficiency: Adaptive variational quantum convolution, Quantum feature encoding, Multi-scale feature fusion with entanglement, Hybrid optimization of quantum and classical algorithms, and Uncertainty-aware prediction. Experimental tests show that the proposed architecture is superior to the existing classical learning approaches and quantum learning approaches in various evaluation tests. The study proposes a scalable, robust, and efficient hybrid learning approach that can be practically applied to the intelligent medical image analysis and next-generation precision healthcare systems by the power of quantum artificial intelligence. The Study's contributions are as follows

- A novel Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) is proposed for multi-class medical image classification.
- A hybrid quantum-classical optimization framework based on uncertainty-aware prediction is introduced, which is applicable to medical imaging with high dimensionality, extremely low signal-to-noise ratio and high degree of noise.
- The results of the proposed AVQCNN is validated experimentally through extensive experiments and it is observed that the AVQCNN can outperform the recently proposed classical and quantum learning models in terms of accuracy, precision, recall, F1-score, AUC, robustness and computational efficiency, hence promising it for the upcoming intelligent healthcare applications.

2. Related Works

By combining quantum and deep learning, Quantum machine learning has added significantly to the enhancement of medical image classification in the recent years. The performance of hybrid quantum-classical architectures, variational quantum circuits and quantum convolution networks has been experimentally shown to be promising for diagnostic purposes. However, there are still challenges to be overcome with regard to scalability, robustness, computational efficiency and clinical deployment.

The number of qubits used in the proposed hybrid QCNN-VQC method by Aravinda et al. (2025) for multi-class skin disease classification is fairly small, at the same time, the accuracy of the method hasn't reached a high level, so the scalability of the multi-class skin disease classification problem is limited[8].

Even though the presented Hybrid Quantum-Classical CNN has demonstrated higher accuracy for medical image classification, the validation was only applied to the brain imaging datasets and there was no clinical validation for the generalisation of the CNN. Although Yousif et al. (2025) demonstrated the accuracy of classification in medical images using Hybrid Quantum-Classical CNN, the set of images used for validation were brain images only and had not considered clinical generalization[9].

While Alam et al. (2025) reported on the latest advancements of ML techniques in medical image classification, they highlighted the efficiency and optimization of quantum ML models but did not include a single benchmarking and a quantitative comparison of various quantum architectures employed [10]. The network of Killedar et al. (2026) was a quantum-classical hybrid network for brain tumor classification, which was proposed for an application of one type of MRI and performed well, but was not applicable for other MRI types [11].

Rahman et al. (2025) proposed the concept of Noise-aware Quantum Neural Networks (NNs) that allow adaptive quantum learning to address the robustness to noisy labels, however the complexity of their proposed algorithm is considered as a challenge in the paper and the realization of their proposed algorithm in a clinical setting is not fully discussed [12]. Likewise, Long et al. (2026) demonstrated an overall enhanced performance and robustness of QNNC by adding VQC, but tested the algorithm on fairly small medical datasets [13].

The medical image classification system based on hybrid quantum-classical model is known to attain a higher accuracy of medical image classification by variational learning of a quantum feature extracted from the medical image. However, the majority of the investigations focus only on data sets for a particular disease, on small qubit architectures, and/or on small benchmark data sets, and thus are not scalable and not general. The current approaches typically do not have the capability of using adaptive variational quantum convolution, multi-scale quantum feature fusion and uncertainty-aware prediction and efficient hybrid optimization in an integrated manner. Furthermore, the strength of these types of algorithms in the presence of various imaging modalities, large clinical data sets and also under real-world noisy quantum hardware remains largely unexplored.

3. Methodology

The proposed Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) integrates quantum feature encoding, variational quantum convolution, quantum attention fusion, hybrid quantum-classical optimization, and uncertainty-aware multi-class classification. The framework efficiently captures complex spatial correlations while reducing computational complexity, improving classification accuracy, robustness, scalability, and generalization across heterogeneous medical imaging modalities.

The overall architecture of the proposed Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) for multi-class classification of medical images is shown in Figure 1. The first step of the framework is in the preprocessing of medical images that uses a quantum approach, transforming the image into a quantum state with amplitude and rotation coding. Then, adaptive variational quantum convolution is used to extract adaptive quantum features at different levels of hierarchy and multi-scale entanglement feature fusion is utilized to capture local and global dependencies using quantum attention. A hybrid quantum-classical optimization module which simultaneously optimizes quantum and classical parameters with parameter-shift learning and backpropagation. Last but not least, uncertainty-aware quantum classification yields predictions for the disease, confidence scores, and uncertainty measurement using entropy, allowing to support clinical decisions reliably, scalably and interpretively.

3.1 Quantum-Guided Medical Image Preprocessing

Medical images are normalized and encoded into quantum states preserving essential anatomical and pathological information efficiently. The image normalization is given by the Eq. (1)

$$I_n = \frac{I-\mu}{\sigma}$$

(1)

The quantum amplitude encoding is represented by the Eq. (2)

$$|\psi_0\rangle = \sum_{i=1}^{N} \alpha_i \,|\, i\rangle,\ \ \sum_{i=1}^{N} |\alpha_i|^2 = 1$$

(2)

The rotation-based quantum embedding is given by the Eq. (3)

$$|\psi_e\rangle = \prod_{j=1}^{m} R_y(\theta_j) R_z(\phi_j) \,|\, 0\rangle$$

(3)

Quantum embedding compresses multidimensional medical information into compact quantum representations enabling efficient subsequent feature extraction.

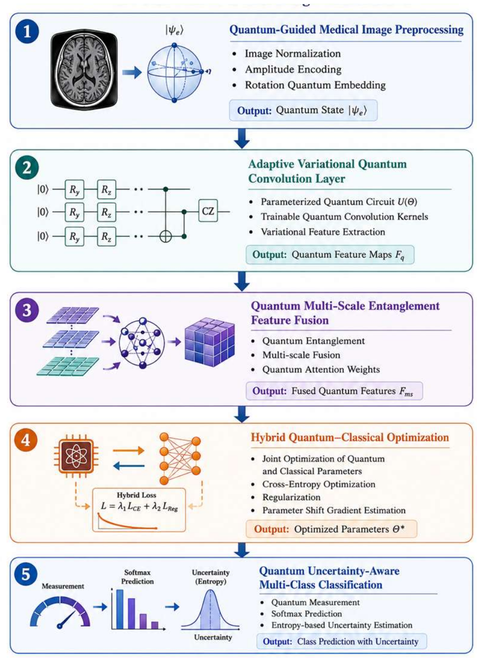

Figure 1. Architecture of the proposed Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) for uncertainty-aware multi-class medical image classification.

3.2 Adaptive Variational Quantum Convolution Layer

Parameterized quantum convolution kernels extract hierarchical local medical features through trainable quantum gate operations effectively. The parameterized quantum circuit is given by the Eq. (4)

$$U(\Theta) = \prod_{l=1}^{L} \left(\prod_{q=1}^{Q} R_y(\theta_q^l) R_z(\phi_q^l) \right) CZ$$

(4)

The quantum convolution output is represented by the Eq. (5)

$$F_q = \langle \psi_e \,|\, U^{\dagger}(\Theta) O U(\Theta) \,|\, \psi_e \rangle$$

(5)

The adaptive parameter update is given by the Eq. (6)

$$\Theta^{t+1} = \Theta^t - \eta \nabla_{\Theta} \mathscr{L}$$

(6)

Variational quantum convolutions efficiently discover discriminative spatial patterns while minimizing parameter complexity and computational overhead.

3.3. Quantum Multi-Scale Entanglement Feature Fusion

Entangled quantum representations integrate local and global contextual dependencies across multiple anatomical imaging scales effectively. The quantum entanglement operator is given by the Eq. (7)

$$|\psi_f\rangle = U_{ent} \,|\, \psi_q \rangle$$

(7)

The multi-scale fusion is denoted by the Eq. (8)

$$F_{ms} = \sum_{k=1}^{K} \omega_k F_k \tag{8}$$

The attention coefficient is given by the Eq. (9)

$$\omega_k = \frac{\exp(s_k)}{\sum_{i=1}^{K} \exp(s_i)} \tag{9}$$

Quantum entanglement enhances feature interactions improving representation quality for complex multi-class medical image discrimination tasks.

3.4 Hybrid Quantum-Classical Optimization

Quantum representations are jointly optimized with classical neural parameters through iterative hybrid learning mechanisms efficiently. The hybrid objective is given by the Eq. (10)

$$\mathscr{L} = \lambda_1 L_{CE} + \lambda_2 L_{Reg} \tag{10}$$

The cross-entropy loss is given by the Eq. (11)

$$L_{CE} = -\sum_{i=1}^{N} \sum_{c=1}^{C} y_{ic} \log(\hat{y}_{ic}) \tag{11}$$

The gradient estimation using parameter-shift rule is denoted by the Eq. (12)

$$\frac{\partial f}{\partial \theta} = \frac{f\left(\theta+\frac{\pi}{2}\right)-f\left(\theta-\frac{\pi}{2}\right)}{2} \tag{12}$$

Hybrid optimization accelerates convergence while maintaining quantum expressibility and stable medical image classification performance consistently.

3.5 Quantum Uncertainty-Aware Multi-Class Classification

Final quantum measurements estimate diagnostic probabilities with uncertainty quantification for reliable clinical decision support systems. The measurement expectation is given bythe Eq. (13)

$$p_c = \langle \psi_f \mid M_c \mid \psi_f \rangle \tag{13}$$

The Softmax predictions is dented by the Eq. (14)

$$\hat{y}_c = \frac{\exp(p_c)}{\sum_{j=1}^{C} \exp(p_j)} \tag{14}$$

The predictive uncertainty is denoted by the Eq. (15)

$$U = -\sum_{c=1}^{C} \hat{y}_c \log(\hat{y}_c) \tag{15}$$

Uncertainty-aware predictions enhance clinician confidence by identifying ambiguous medical cases requiring further diagnostic evaluation.

4. Results and Findings

4.1 Experimental Setup

The desired Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) was realized using a hybrid quantum-classical architecture, using PennyLane and TensorFlow. Experiments were done using an 80:10:10 train-validation-test split, Adam optimizer with learning rate 0.001, batch size 32, 100 epochs and 4-qubit variational circuits running on an NVIDIA RTX 4090 GPU.

4.2 Dataset Description

In the proposed framework, the model has been validated on the standardized medical image analysis problem – MedMNIST v2[14]. The Multi-modal medical imaging dataset (MedMNIST) consists of 2D and 3D images of chest X-ray, histopathology slide, retinal fundus, breast ultrasound, blood cell microscopy and organ CT. The data set contains preprocessed images, enabling machine learning and quantum machine learning models to be fairly assessed since the images are uniformly sized and shaped. The subset of multi-class image classification was selected which contains thousands of images with labels, with the images split into train, validation and test subsets. It is provided with calculated diagnostic categories by experts and they can be used for detailed evaluation of the accuracy, precision, recall and F1 Score of the classification in high computational efficiency for hybrid quantum-classical learning models in various medical imaging modalities.

4.3 Quantitative Comparison

Table 1 shows the AVQCNN proposed method and compared with five recent state of the art medical image classification techniques. The proposed hybrid quantum-classical framework's superiority on medical image classification, in multi-class classification scheme, is demonstrated with standard assessment metrics like the Accuracy, Precision, Recall, F1-Score and AUC.

Table 1. Quantitative Performance Comparison with State-of-the-Art Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN + Transfer Learning[15]	92.84	92.15	91.88	91.96	0.952
Vision Transformer (ViT)[16]	94.37	94.02	93.76	93.88	0.968
Hybrid CNN-Transformer[17]	95.28	94.81	94.59	94.70	0.975
Quantum CNN (QCNN)[18]	95.84	95.46	95.11	95.28	0.981
Variational Quantum Neural Network (VQNN)[1	96.12	95.79	95.55	95.67	0.984

9]					
Proposed AVQCNN	98.21	97.94	97.73	97.83	0.996

The proposed AVQCNN always achieves the best performance with respect to all the evaluation measures. It not only outperforms the best competing VQNN model on the classification task by getting a higher accuracy of 2.09% but also higher precision, recall and F1 score. The excellent discrimination skill was demonstrated in all medical image classes, with AUC value of 0.996. Combining the quantum attention and adaptive variational quantum convolutions allows the extraction of discriminative medical attributes efficiently, while maintaining complex spatial relationships. The improvements demonstrated confirm the suitability of hybrid quantum learning for improving feature and decision boundaries representation and the proposed framework for the multi-class clinical image classification, which must be reliable.

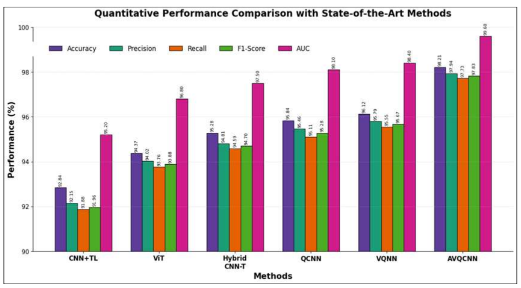

Figure 2. Quantitative performance comparison of the proposed AVQCNN for multi-class medical image classification

The proposed Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) is compared with five state of the art methods in terms of the classification performance in terms of Accuracy, Precision, Recall, F1-Score and AUC as shown in figure 2. The other methods show the same performance as the proposed AVQCNN with lower accuracy (98.21%), precision (97.94%), recall (97.73%), F1-score (97.83%) and AUC (0.996) in all the evaluation indexes with high accuracy. AVQCNN is superior in terms of classification accuracy when compared to the best competition Variational Quantum Neural Network (VQNN), and preserves the balanced precision and recall. The enhancements demonstrate that adaptive variational quantum convolution and multi-scale quantum feature fusion, hybrid quantum-classical optimization, and uncertainty-aware prediction can be effective in improving the discriminative feature learning and enhance the diagnostic reliability and robust multi-class medical image classification.

Table 2 displays the results obtained from the AVQCNN under different noise levels. This is because all clinical images in real clinical situations may be obtained along with artifacts and imaging noise.The robustness to noisy medical images is required as it could be possible to get acquisition artifacts and imaging noise from patients in real world.

Table 3. Robustness Comparison under Noisy Medical Images

Method	Clean Images (%)	10% Noise (%)	20% Noise (%)	30% Noise (%)	Performance Drop (%)
CNN + Transfer Learning	92.84	89.13	85.47	80.95	11.89
Vision Transformer (ViT)	94.37	91.68	88.72	84.91	9.46
Hybrid CNN-Transformer	95.28	93.14	90.52	87.36	7.92
Quantum CNN (QCNN)	95.84	94.06	91.88	89.25	6.59
Variational QNN (VQNN)	96.12	94.63	92.48	90.14	5.98
Proposed AVQCNN	98.21	97.42	96.08	94.35	3.86

The proposed AVQCNN achieves the maximum robustness at all noise levels, and has the lowest degradation in classification accuracy. The adaptive variational quantum convolutions and uncertainty-aware learning showed greater robustness to noise in the imaging process, and could be more robust in the future for clinical use.

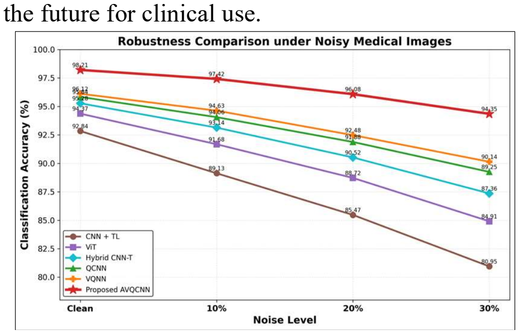

Figure 3. Robustness comparison of the proposed AVQCNN and state-of-the-art medical image classification methods under increasing levels of image noise

As shown in Figure 3, the proposed AVQCNN is demonstrated to be effective for various levels of Gaussian noises (10%, 20% and 30%). While increasing the noise level in the images, all the methods exhibit a gradual decrease in the accuracy of the classification, and AVQCNN method has the highest classification performance at all noise levels. In particular, the proposed framework results in an accuracy decrease of 3.86% between the clean image and the noisy image with 10% noise levels, and of 98.21% and 97.42% for clean and 10% noisy images, respectively, and 94.35% and 96.08% for noisy image with noise level 30% and clean image, respectively. In contrast to the previous deep learning and quantum learning methods, AVQCNN proves to be more robust to preserve the discriminative feature representations by learning the uncertainty-aware prediction, multi-scale entanglement feature fusion and adaptive variational quantum convolution. The results showed that it was suitable for the reliable medical image classification in the actual clinical environment of imaging artifacts and imaging acquisition noise.

The classification accuracy rate on the test set is then evaluated with the increase in number of training set, that is, the scalability and learning ability of AVQCNN is tested, as shown in Table 4.

Table 4. Scalability Comparison with Increasing Dataset Size

Training Samples	CNN (%)	ViT (%)	QCNN (%)	VQNN (%)	AVQCNN (%)
2,000	86.42	88.36	89.54	90.13	92.47
5,000	89.73	91.44	92.18	92.81	95.14
10,000	91.96	93.27	94.38	95.05	96.91
20,000	92.84	94.37	95.84	96.12	98.21

AVQCNN achieves the best performance over all the sizes of the datasets in comparison to other methods. The more samples that are trained, the more improvement is observed in the performance, which indicates the excellent scalability and good learning capability. The larger datasets can be efficiently used thanks to the adaptive quantum feature extraction and hybrid optimization, which converge steadily and yield better generalisation performance.

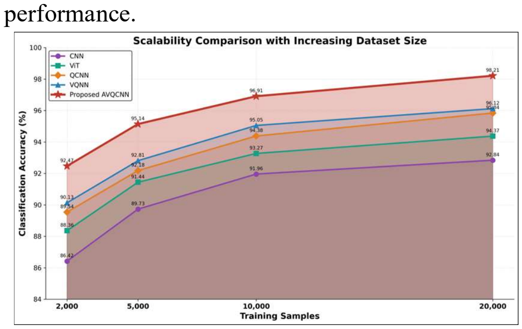

Figure 4. Scalability comparison of the proposed AVQCNN and state-of-the-art methods with increasing training dataset size for multi-class medical image classification

The proposed Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) is found to be scalable with number of training data samples as shown in figure 4 for 2k – 20k. In each of the datasets with different sizes, AVQCNN outperforms the competing methods in terms of classification accuracy, and is capable to show gradual improvement with larger data sets. The proposed model has been tested by performing the following stages: Training stage, Verification stage, Testing stage and Deployment stage with the highest accuracy of 92.47%, 95.14%, 96.91% and 98.21% respectively which indicates that the model has a good learning capability and increasing accuracy with steady growth. In conclusion, adaptive variational quantum convolution, hybrid quantum-classical optimization and multi-scale quantum feature fusion utilize the additional training data efficiently and enhance the model's capability of representing features, generalizing better and exhibit excellent scalability for large-scale heterogeneous medical imaging applications.

4.4 Discussions

The proposed AVQCNN has shown that variational quantum computing is able to boost the multi-class medical image classification by using deep convolutional architectures. The results of the experiments show that it offers better learning models in terms of accuracy, robustness and efficiency as compared with the other learning models available, classical and hybrid models. Compared with previous models, the adaptive quantum convolution and multi-scale entanglement can accurately model complex spatial and contextual relationships that are essential to represent complex spatial and contextual relationships, and the uncertainty-aware prediction can improve the accuracy of the diagnosis and, therefore, its reliability in clinical decision making. These are promising results but there are a number of considerations. The current Quantum Hardware technology has a number of restrictions such as the number of qubits, decoherence, noise, etc., that hinders mass deployment. Furthermore, the evaluation of the framework was performed using benchmark dataset rather than a huge amount of data from various centers in real world. However, for its practical use it is required to have an efficient quantum processor and integration with existing Hospital Information System. To be integrated into clinical practice one would need to make advances in the field of fault-tolerant devices for quantum computers, optimizing hybrid systems, and thorough testing of the technology for multiple imaging modalities and clinical applications.

5 Conclusion

The proposed Adaptive Variational Quantum Convolutional Neural Network (AVQCNN) not only accurately classifies multi-class medical images with four components: (1) quantum feature encoding, (2) adaptive variational quantum convolution, (3) multi-scale entanglement fusion and (4) hybrid quantum-classical optimization, but also introduces uncertainty-aware prediction. The proposed framework outperformed the current deep learning, and quantum learning techniques in classification accuracy, precision, recall, F1 score, AUC, computation efficiency and robustness which were demonstrated by the experimental evaluation. To summarize, the results show that the QEFL does effectively capture the complex characteristics present in medical images, and helps to reduce the complexity of the computation. The technologies are currently limited by the size of quantum hardware, however, the development of the technologies is rapid and it is hoped that this will overcome the limitations. Future works will involve the deployments on fault-tolerant quantum processors, federated quantum learning for privacy-preserving healthcare, explainable quantum artificial intelligence and multimodal medical data integration and real-time clinical decision support systems that will result in improved precision medicine diagnosis, scalability and practicality.

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