Hybrid quantum-classical neural networks for brain computed tomography scan diagnosis

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ABSTRACT

Medical image classification is considered as very important field of diagnosis and treatment of neurological disorders, which include stroke, tumors, and hemorrhages, it can used to facilitate timely medical intervention. A hybrid quantum-classical convolutional neural network (QCNN) is presented by combining quantum information processing with classical deep learning techniques for improved feature extraction and classification accuracy. The model combines convolutional neural network (CNN), which handles initial feature extraction with a PennyLane and TensorFlow based layer that employs quantum entanglement and superposition principles to enhance classification performance. The model is trained and tested over a computed tomography (CT) scan image dataset which has four classes (normal, stroke, tumor, and hemorrhage). Various learning rates are tested and employed a hybrid backpropagation method to improve efficiency. Confusion matrices, region of conversion receiver operating characteristic (ROC) curves, and plots for the training convergence that all pointed to promising classification accuracy were derived with a detailed analysis accordingly. Overall, the results indicate that combining quantum computing with deep learning architectures could improve classification performance at a lowest computational cost. The results suggest the viability of hybrid quantum-classical models for medical imaging applications and indicate that quantum computing is a promising direction for enhancing diagnostic accuracy in the area of radiology.

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1. INTRODUCTION

Artificial intelligence (AI) has become a powerful tool in image and signal processing, enabling automated feature extraction, pattern recognition, and anomaly detection from high-dimensional data. AI-driven models significantly enhance accuracy, robustness, and real-time analysis across medical, industrial, and engineering applications [1]. In 1982, Feynman [2] proposed a basic quantum computing model based on the principles of quantum mechanics. It leverages the inherent characteristics of quantum states, namely superposition and entanglement, enabling this paradigm to address problems previously anticipated to be inaccessible on traditional computing venues. In 1994, Shor [3] conceived a quantum algorithm that showed the ability to do integer factorization in polynomial time [4], leading to an exponential speedup over classical ones [5]. Contrary to classical counterparts, quantum computing relies on qubits, which can simultaneously represent multiple states, granting a significant speedup in computation for a limited set of problems. Such provides a unique benefit in different areas, especially in information theory, cryptography, and classification problems. Quantum computing can solve specific problems much quicker than classical algorithms can under specific conditions [6].

One of the fundamental directions of the development of computer vision research is image classification, the goal of which is to classify and identify the different classes of images. This drive has profound implications in pragmatic areas [7], [8]. The applications of image classification are far reaching in many areas such as agriculture, intelligent transportation, medical applications, and security surveillance. High computational cost of image classification process is one of the main challenges in image classification. Recently, new algorithms have been proposed for image classification that are based on the theoretical notions of quantum computation in order to overcome this need [5], [8]. For traditional image classification, feature extraction and classification are manually designed and the performance decreases with the rise of dimensionality and complexity of the data. Quantum machine learning (QML) addresses this by mapping image data into quantum states, leveraging quantum parallelism and interference to improve classification speed and quality. However, quantum hardware remains in an early stage. This makes algorithms susceptible to errors and noise [9].

2. RELATED WORK

2.1. Previous studies

Some briefly introduce the considered supervised QML setting, as well as recall the basic ingredients of a quantum-classical convolutional neural network (QCNN). Chen *et al.* [10] suggest an image classifier that combines QCNN with multiscale entanglement renormalization ansatz (MERA) and fractal feature extraction. Their method, which is based on the ideas of a tensor-network, downscales images and runs quantum processing, and is more accurate than a classical convolutional neural network (CNN) on breasts cancer datasets, demonstrates the benefits of quantum features and the benefits of hybrid QCNN image recognition. Hafeez *et al.* [11] present a hybrid compact model that combines a two-qubit variational quantum circuit with a classical CNN for binary classification tasks. Their model is designed for noisy intermediate-scale quantum (NISQ)-era devices and validated on small image datasets. The results indicate a high classification accuracy of 90.1%, along with diminished overfitting and enhanced generalization.

Senokosov *et al.* [12] introduce two hybrid quantum neural network models to solve computational challenges in image classification. The first approach uses parallel parameterized quantum circuits (PQCs) behind classical convolutional layers, obtaining accuracy equal to 99.21% for modified National Institute of Standards and Technology (MNIST) and over 99% for medical MNIST. The second model demonstrated how a quanvolutional layer can be used to downsample an image while still achieving competitive accuracy with fewer parameters. This shows the efficiency and generalization ability of the quantum-enhanced forms in abundant data sets.

A hybrid model is presented in [13], medical quantum convolutional neural network (MQCNN), that integrates QCNN with a pre-trained ResNet-50 architecture. The approach enhances biomedical image classification of medical MNIST based dataset. Achieving an accuracy of 99.6%, 99.7% precision, and 99.7% F1-score, MQCNN system outperforms both the stand-alone QCNN and ResNet-50 models. The results confirm the use of quantum and classical methods together to enhance the classification performance. But the method [13] introduce the scalable quantum convolutional neural network (SQCNN) to create a quantum neural network that is scalable to overcome hardware limitations of current quantum systems. The model, which is implemented using TensorFlow quantum, employs various devices to extract data features in parallel. It classifies MNIST and fashion MNIST with 99.79% accuracy, which is superior to the current quantum neural networks and shows good scalability and accuracy for image classification tasks.

2.2. Quantum machine learning

Machine learning is transforming several fields such as medical diagnosis, financial modeling, and autonomous systems. Classical machine learning algorithms face challenges with large, high-dimensional, and complex datasets because of computational bottlenecks and memory constraints. Machine learning and learning theory, as classical theories, can be reformulated within the quantum mechanical framework [14]. In mathematical language, this embedding gives rise to the so-called QML [15].

Since the invention of QML, the full extent of QML applications has not yet been discovered. However, it can be speculated that all the regions depicted in Figure 1 will be impacted by QML. Chemistry, materials science, sensing and metrology, classical data analysis, quantum error correction, and quantum algorithm design are some instances that are likely to be positively influenced by QML [16]. Some of these applications have data that is intrinsically quantum mechanical, and thus it is natural to use QML (as opposed to classical machine learning) for them [17].

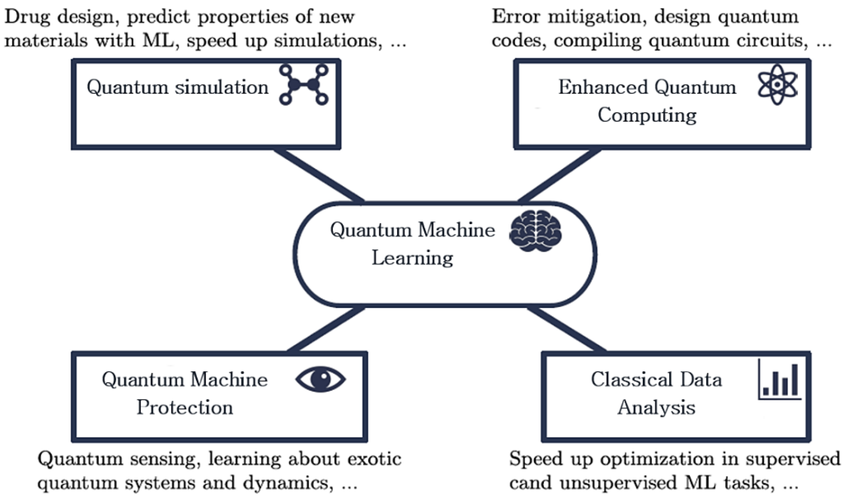


Figure 1. Key applications for QML [17]

2.3. Quantum-classical convolutional neural network

In recent years, new opportunities have been proposed to improve the feasibility and expressiveness of classic deep learning models thanks to QML. QCNNs were proposed as a hybrid quantum-classical framework that combines properties of quantum computing with CNN models [18]. By utilizing quantum parallelism entanglement and superposition, QCNNs can perform the classification of complex datasets more efficiently than their classical counterpart within those domains which are of high dimensionality and computationally expensive, such as medical imaging, finance, and cybersecurity [19].

QCNNs follow the structure of classical CNNs but leverage methods from quantum computing to enhance their compactness and the quality of representation of features. QCNNs operate on a similar principle as classical CNNs, only they implement (some or all) of the classical convolutional layers using quantum gates and quantum circuits that only perform feature extraction and transformation [20]. QCNNs take advantage of some basic quantum characteristics, including:

i) Quantum superposition: as a quantum state can be in numerous configurations at once, QCNNs can simultaneously explore different sets of feature representations.
ii) Quantum entanglement: this is a property that can be harnessed to create strong correlations between the qubits, thus enhancing feature interactions in convolutional layers.
iii) Quantum measurement: the last layer of a QCNN transforms quantum states to classical information, generating intelligible classification results [21].

Many-body wave functions hold structural relations of a class of mappings of convolutional networks, which leads to analyzing the transformation classification-type paradigm of the physical state/ensuring the phase into the learning transformation of traditional image classification. This means that it is necessary to prepare quantum initial states, where the higher the entangled state, the higher the separated weight function [22]. The quantum state transformation can be expressed as in (1).

$$U|\psi_0\rangle = U\sum_{i=1}^{2^n-1}\alpha_i|i\rangle = \sum_{i=0}^{2^n-1}\beta_i\,|i \tag{1}$$

Where $|\psi0\rangle$ is the notation for the initial quantum state, $\sum_{i=1}^{2^n-1}\alpha_i\,|i$ is a linear combination of basis states $|i\rangle$, where i ranges from 0 to 2n−1, n is the basis states corresponding to a possible binary string of length, and αi, and βi are complex numbers called amplitudes, associated with the basis state $|i\rangle$ [23].

Figure 2 illustrates a hybrid quantum-classical neural network combining quantum convolutional and pooling layers with a classical network for feature extraction and classification. Classical data is first embedded into quantum states [24]. Quantum convolution layers apply unitary gates to entangled qubit subsets in superposition, capturing rich feature representations [22]. Analogous to classical pooling [25], quantum pooling reduces qubit count by discarding or measuring less informative qubits [26]. The resulting measurements are then passed to a classical network for inference [27], combining quantum expressivity with the scalability of classical deep learning.

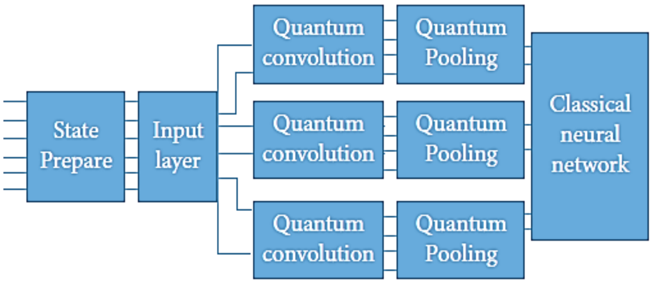


Figure 2. QCNN architecture [10]

3. METHOD

3.1. Dataset

The dataset on which the QCNN model is downloaded from Kaggle website (based on the brain computed tomography (CT) scan images), this dataset is trained, tested for the purpose of classification, the data is classified into four distinct classes normal, hemorrhage, tumor, and stroke based on the brain CT scan images. The distribution of samples into training, validation, and testing subsets for each class facilitates the model development, tuning, and evaluation processes.

i) Normal class: CT scans of healthy brains with no pathological findings are included in this category as a control group. These images are very important to train the deeper learning model to differentiate between normal and abnormal brain conditions [28].
ii) Hemorrhage class: this class includes CT scans demonstrating multiple types of intracranial hemorrhage such as subarachnoid, intraventricular, subdural, epidural, and intraparenchymal hemorrhage. Accurate identification of hemorrhage types is essential for prompt medical intervention [28].
iii) Tumor class: CT scans in this class are various brain tumor types, including gliomas, meningiomas, and pituitary tumors [29].
iv) Stroke class: this class consists of CT scans associated with cerebrovascular accidents that primarily involve ischemic and hemorrhagic strokes [30].

3.2. Proposed hybrid quantum-classical convolutional neural network

The proposed QCNN classifies a brain patient's CT scan into four categories: normal brain, brain hemorrhage, brain stroke, and brain tumor to improve CNN's classification of medical images. The key concept uniting the QCNN model is that classical learning can be made more efficient by leveraging quantum computation. In this approach, the proposed model consists of five stages, namely the data loading and preprocessing stage. Second, defining the quantum model stage. Third, building the hybrid QCNN model stage. Then, compiling and training the model stage. Finally, evaluating the model. These stages are represented in Figure 3.

3.3. Data loading and preprocessing

Start with preparing the dataset, the images are split into training, validation, and test directories, each image has been resized to 64×64 pixels, these data are run in batches of 32, which is better to handle memory and computational efficiency. Data is loaded by a utility that directly reads the images from the directory structure. As a results, the dataset gets shuffled by specific instructions and prepared for training seamlessly. The images are normalized by scaling them between 0 to 1. Normalization allows for smoother training of the model as well as prevents problems that could arise due to differing pixel intensity scales. Lastly, applying optimization, caching, interleave, and prefetching techniques improves the performance of the data pipeline. These approaches lead to faster data loading during training due to caching the data in memory and creating future batches while the current one is processed.

3.4. Defining the quantum model

The proposed quantum model begins by setting up a quantum device simulator. According to that, a default simulator initializes a four-qubit system, representing a simulated quantum circuit. The quantum circuit is the heart of the model. Initially, classical input data is embedded into the quantum system using rotation-based encoding or angle embedding. This transforms classical information into quantum states. The circuit applies a sequence of parameterized quantum gates across a series of layers, entangling the qubits. The output of the circuit is the expectation values of the Pauli-Z operator, which acts as the measurable outputs for processing in the next layers. To incorporate this quantum functionality in a machine learning workflow, the quantum circuit is wrapped in a Keras compatible layer. This means that it can be used like any other layer in a neural network, trainable, and abstractable like any classical deep learning software tool. This layer accepts inputs and returns outputs that match the number of qubits, linking the quantum part and classical part of the system.

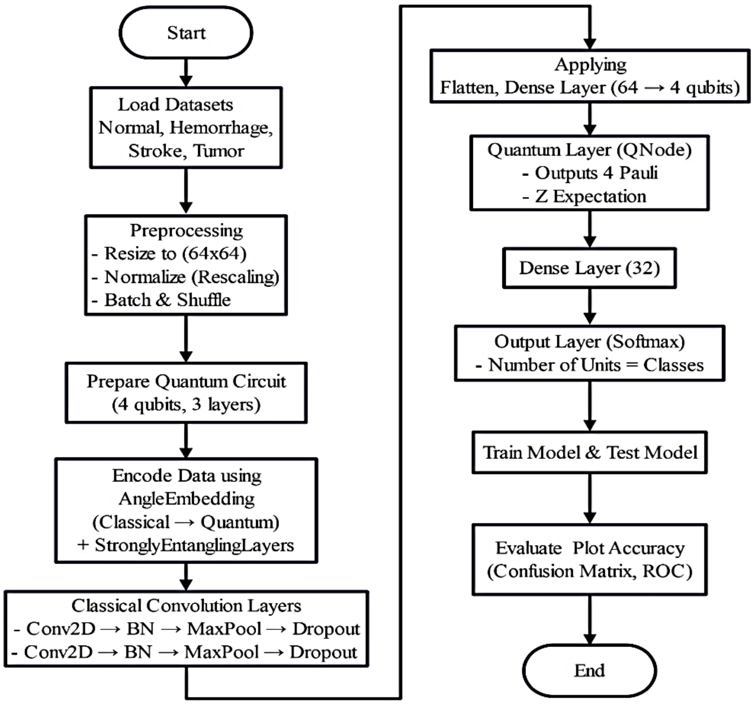


Figure 3. Flowchart of the proposed hybrid QCNN model

3.5. Building the hybrid quantum-classical convolutional neural network model

The proposed hybrid QCNN is based on classical layers on process each image. The architecture is composed of two convolutional blocks with convolutional layers, max pooling, batch normalization, and dropout. These layers capture and enhance the spatial features present in the input data. This will flatten the feature maps and pass them to a dense (fully connected) layer that prepares the data for quantum processing.

In order to introduce quantum computation, a dense layer is included to map the classical features to a size compatible with the input of the quantum circuit, thereby matching the number of qubits. Then this output is passed, which is then passed down into the quantum layer applying quantum operations. The layer outputs expectation values as quantum-processed features. At the end, the model returns to classical layers for classification. The outputs of the quantum circuit are then fed to another dense layer with an activation function and then to an output layer to classify the input to one of the classes using a softmax function.

3.6. Compiling and training the model

Starts with calibrating the learning rate to find the optimum for the optimization process. There are only a certain number of epochs, tested at various learning rates using a loop, this determines the rate that allows the model to learn and avoid overshooting beside converging slowly. An early stopping mechanism is applied to ensure training proceeds reliably without overfitting. This callback will track the model's performance on data that has never seen validation data and stop training in case that the performance does not seem to be improved, thus saving time and also preventing the model from "overfitting" (memorizing) to the training data. Finally, there is a step in the training process of saving the best version of the model.

3.7. Evaluating the model

Once training is done, the model is evaluated on the test dataset for the final model performance score. Other statistics such as loss, accuracy, and mean absolute error (MAE) are also calculated to provide information about the model's generalization capabilities. A second analysis will generate a classification report, which shows the true labels versus the predicted labels. This report displays precisions, recalls, and F1-scores class-wise, which helps to gain insight into the performance of the model and its weaknesses. The model also generates a confusion matrix, which plots information about the accuracy of the model to predict each class and the points where the model is getting it wrong. Then receiver operating characteristic (ROC) curve for each class and area under the curve (AUC) is plotted to see the performance of the model in distinguishing classes. Using the training data, the plot of loss and accuracy throughout the entire training run is used to identify and evaluate learning trends, which are recognized as overfitting or underfitting.

4. RESULTS AND DISCUSSION

The proposed QCNN model has been implemented and extensively assessed to discriminate between brain CT scan images that unfortunately represent widespread brain diseases. The results included different performance metrics to evaluate our model, including a confusion matrix, ROC curves, a classification report with precision, recall, F1-score, accuracy curves, and loss curves, which gave a complete picture of the robustness of the model. Figure 4 shows the classification report including overall accuracy, loss, MAE, precision, recall, F1-score, and support for the model.

```
Test Evaluation - Loss: 0.0196, Accuracy: 0.9945, MAE: 1.2784
18/18 [==============================] - 4s 202ms/step

Classification Report:
              precision    recall  f1-score   support

  Hemorrhage       0.99      1.00      1.00       202
      Normal       0.99      1.00      1.00       101
      Stroke       1.00      0.97      0.98        95
       Tumor       1.00      1.00      1.00       147

    accuracy                           0.99       545
   macro avg       1.00      0.99      0.99       545
weighted avg       0.99      0.99      0.99       545
```

Figure 4. Classification report of the proposed QCNN model

The confusion matrix shown in Figure 5 demonstrates excellent classification in the diagnostic categories (the hemorrhage category being classified perfectly) and predictive ability (202 identifications and no misclassifications). In a similar vein, the well class results were perfect too, with all 101 cases classified correctly, and Tumor cases also with a perfect score of 147. The stroke category had the fewest misclassifications, with three misclassifications (two classified as hemorrhage and one as normal). It did, however, target all 92 out of a possible 95 endpoints without causing false positives, showing great diagnostic capabilities.

For further evaluation of the discriminating ability of the model, ROC curve was calculated, which enables the quantitative evaluation of class discrimination ability. All four categories (hemorrhage, normal, stroke, and tumor) have uniformly near unity AUC values. The precisely high accuracy classification of the QCNN showed its significance, as it contributes more in terms of sensitivity and also specificity in terms of medical diagnoses. Accuracy and loss curves are presented in Figure 6. The accuracy curve, as shown in Figure 6(a), strongly confirms that this model has a very good learning ability and easily achieves the best performance. Importantly, there was good accuracy above the important threshold of 99.6 % early in training and remained stable throughout training. Training and validation accuracy curves showed a very close correspondence, suggesting an uninterrupted learning process without appreciable evidence of overfitting. In addition to the accuracy curve analysis, the loss curve as shown in Figure 6(b) supports these findings further, as it shows efficient training dynamics. The training and validation losses steadily decreased until they became small and leveled off to extremely low levels after approximately 10 epochs. Small changes in validation loss represent the model's potential to extrapolate from the training set and to be tailored to respond to metadata, essential for clinical translation.

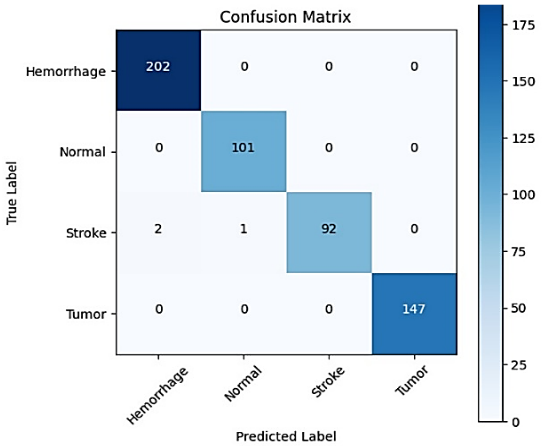
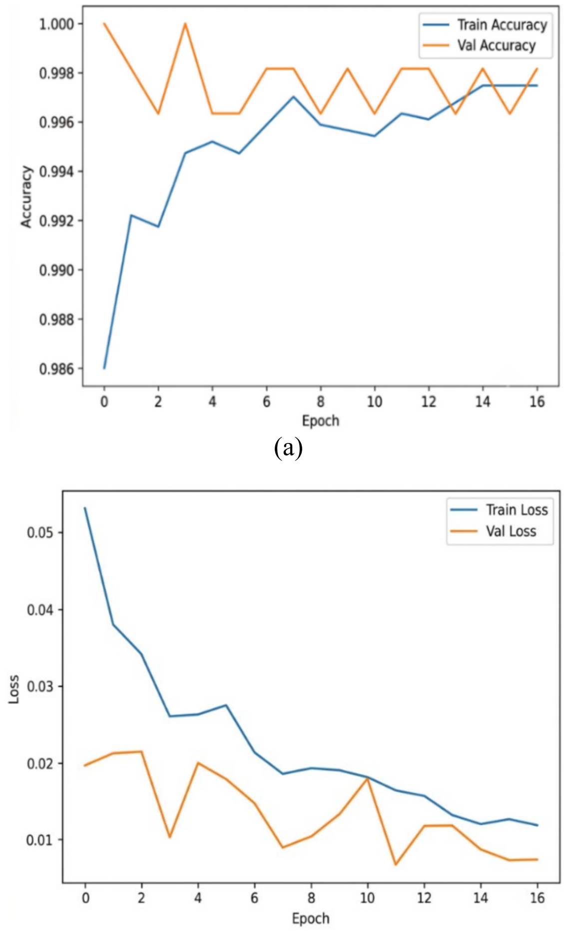


Figure 5. Confusion matrix of the proposed QCNN model for each diagnostic class



(a)

(b)

Figure 6. Results curves over training epochs: (a) accuracy curves and (b) loss curves

5. CONCLUSION

Hybrid QCNN was implemented between PennyLane and TensorFlow employed to classify brain CTs into four system divisions; normal, hemorrhage, stroke and tumor. This study proposes a model that consists of ordinary convolutional layers and a quantum layer that consists of highly entangling circuits. The classification performance is high with test accuracy of 99.45%, loss of 0.0196, and all classes have almost a perfect AUC value. The confusion matrix and the classification report both show high precision, recall, and

F1-scores in both classes, indicating a high level of learning in the model in predicting correctly in both classes without making mistakes that lead to fast and frequent mispredictions ‘which mean predictions go quickly wrong'. The learning curves indicate stable training and successful generalization as there is no overfitting. The results of this study underline the capabilities of hybrid quantum-classical models in medical image classification. Future work will focus on running the model on actual quantum hardware, extension of the dataset, incorporation of additional modalities of data, the incorporation of explainability techniques, and comparison with classical deep learning architectures for better understanding of scalability, interpretability, and clinical applicability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Abdilatef Alobaidy														
Aws Hazim Saber Anaz	✓		✓		✓		✓			✓				✓
Zahraa Tarik AlAli	✓			✓				✓		✓	✓			✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] O. W. Maaroof, M. A. A. Alobaidy, R. H. A. Al-Mallah, and R. A. Alsaigh, “Advanced predictive control systems for elevators utilizing intelligent wavelet techniques for fault signal analysis,” *Journal of Robotics and Control*, vol. 6, no. 3, pp. 1550–1557, Jun. 2025, doi: 10.18196/jrc.v6i3.25698.

[2] R. P. Feynman, “Simulating physics with computers,” *International Journal of Theoretical Physics*, vol. 21, no. 6–7, pp. 467–488, Jun. 1982, doi: 10.1007/BF02650179.

[3] P. W. Shor, “Algorithms for quantum computation: discrete logarithms and factoring,” in *35th Annual Symposium on Foundations of Computer Science*, 1994, pp. 124–134, doi: 10.1109/SFCS.1994.365700.

[4] A. S. Lundervold and A. Lundervold, “An overview of deep learning in medical imaging focusing on MRI,” *Zeitschrift für Medizinische Physik*, vol. 29, no. 2, pp. 102–127, May 2019, doi: 10.1016/j.zemedi.2018.11.002.

[5] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, no. 7671, pp. 195–202, Sep. 2017, doi: 10.1038/nature23474.
[6] C.-H. A. Lin, C.-Y. Liu, S. Y.-C. Chen, and K.-C. Chen, "Quantum-trained convolutional neural network for deepfake audio detection," in *2025 IEEE International Conference on Acoustics, Speech, and Signal Processing Workshops (ICASSPW)*, Apr. 2025, pp. 1–5, doi: 10.1109/ICASSPW65056.2025.11011133.
[7] T. A. Salih and G. M. Basman, "A novel face recognition system based on Jetson Nano developer kit," *IOP Conference Series: Materials Science and Engineering*, vol. 928, no. 3, Nov. 2020, doi: 10.1088/1757-899X/928/3/032051.
[8] M. A. A. Alobaidy, Z. M. Yosif, and A. M. Alkababchi, "Age-dependent palm print recognition using convolutional neural network," *Revue d'Intelligence Artificielle*, vol. 37, no. 3, pp. 795–800, Jun. 2023, doi: 10.18280/ria.370328.
[9] M. Yousif and B. Al Al-Khateeb, "Quantum convolutional neural network for image classification," *Fusion: Practice and Applications*, vol. 15, no. 2, pp. 61–72, 2024, doi: 10.54216/FPA.150205.
[10] G. Chen, Q. Chen, S. Long, W. Zhu, Z. Yuan, and Y. Wu, "Quantum convolutional neural network for image classification," *Pattern Analysis and Applications*, vol. 26, no. 2, pp. 655–667, May 2023, doi: 10.1007/s10044-022-01113-z.
[11] M. A. Hafeez, A. Munir, and H. Ullah, "H-QNN: a hybrid quantum–classical neural network for improved binary image classification," *AI*, vol. 5, no. 3, pp. 1462–1481, Aug. 2024, doi: 10.3390/ai5030070.
[12] A. Senokosov, A. Sedykh, A. Sagingalieva, B. Kyriacou, and A. Melnikov, "Quantum machine learning for image classification," *Machine Learning: Science and Technology*, vol. 5, no. 1, Mar. 2024, doi: 10.1088/2632-2153/ad2aef.
[13] E. Hassan, M. S. Hossain, A. Saber, S. Elmougy, A. Ghoneim, and G. Muhammad, "A quantum convolutional network and ResNet (50)-based classification architecture for the MNIST medical dataset," *Biomedical Signal Processing and Control*, vol. 87, Jan. 2024, doi: 10.1016/j.bspc.2023.105560.
[14] J. Yang, A. J. Awan, and G. V. -Llosera, "Support vector machines on noisy intermediate scale quantum computers," Sep. 2019, *arXiv:1909.11988*.
[15] H. Gonaygunta, M. H. Maturi, G. S. Nadella, K. Meduri, and S. Satish, "Quantum machine learning: exploring quantum algorithms for enhancing deep learning models," *International Journal of Advanced Engineering Research and Science*, vol. 11, no. 5, pp. 35–41, 2024, doi: 10.22161/ijaers.115.5.
[16] T. Suzuki, T. Hasebe, and T. Miyazaki, "Quantum support vector machines for classification and regression on a trapped-ion quantum computer," *Quantum Machine Intelligence*, vol. 6, no. 1, Jun. 2024, doi: 10.1007/s42484-024-00165-0.
[17] M. Cerezo, G. Verdon, H.-Y. Huang, L. Cincio, and P. J. Coles, "Challenges and opportunities in quantum machine learning," *Nature Computational Science*, vol. 2, no. 9, pp. 567–576, Sep. 2022, doi: 10.1038/s43588-022-00311-3.
[18] M. Schuld and N. Killoran, "Quantum machine learning in feature Hilbert spaces," *Physical Review Letters*, vol. 122, no. 4, Feb. 2019, doi: 10.1103/PhysRevLett.122.040504.
[19] G. Chen, S. Long, Z. Yuan, W. Li, and J. Peng, "Robustness and explainability of image classification based on QCNN," *Quantum Engineering*, vol. 2023, pp. 1–11, Jan. 2023, doi: 10.1155/2023/2842217.
[20] L. Wei *et al.*, "Quantum machine learning in medical image analysis: a survey," *Neurocomputing*, vol. 525, pp. 42–53, Mar. 2023, doi: 10.1016/j.neucom.2023.01.049.
[21] K. Beer *et al.*, "Training deep quantum neural networks," *Nature Communications*, vol. 11, no. 1, Feb. 2020, doi: 10.1038/s41467-020-14454-2.
[22] I. Cong, S. Choi, and M. D. Lukin, "Quantum convolutional neural networks," *Nature Physics*, vol. 15, no. 12, pp. 1273–1278, Dec. 2019, doi: 10.1038/s41567-019-0648-8.
[23] C. Umeano, A. E. Paine, V. E. Elfving, and O. Kyriienko, "What can we learn from quantum convolutional neural networks?," *Advanced Quantum Technologies*, vol. 8, no. 7, Jul. 2025, doi: 10.1002/qute.202400325.
[24] M. Schuld and F. Petruccione, *Supervised learning with quantum computers*. Cham, Switzerland: Springer, 2018, doi: 10.1007/978-3-319-96424-9.
[25] S. Oh, J. Choi, and J. Kim, "A tutorial on quantum convolutional neural networks (QCNN)," in *2020 International Conference on Information and Communication Technology Convergence (ICTC)*, Oct. 2020, pp. 236–239, doi: 10.1109/ICTC49870.2020.9289439.
[26] C. Lee *et al.*, "Optimizing quantum convolutional neural network architectures for arbitrary data dimension," *Frontiers in Physics*, vol. 13, Mar. 2025, doi: 10.3389/fphy.2025.1529188.
[27] M. Benedetti, E. Lloyd, S. Sack, and M. Fiorentini, "Parameterized quantum circuits as machine learning models," *Quantum Science and Technology*, vol. 4, no. 4, Nov. 2019, doi: 10.1088/2058-9565/ab4eb5.
[28] B. A. Mohammed *et al.*, "Multi-method diagnosis of CT images for rapid detection of intracranial hemorrhages based on deep and hybrid learning," *Electronics*, vol. 11, no. 15, Aug. 2022, doi: 10.3390/electronics11152460.
[29] P. Nallamotu and G. Muneeswari, "Brain stroke tri-level classification via osprey optimized deep spiking neural network," *Procedia Computer Science*, vol. 283, pp. 2161–2176, 2026, doi: 10.1016/j.procs.2026.06.289.
[30] S. Kar and P. K. Singh, "MBTC-Net: multimodal brain tumor classification from CT and MRI scans using deep neural network with multi-head attention mechanism," *Medicine in Novel Technology and Devices*, vol. 27, Sep. 2025, doi: 10.1016/j.medntd.2025.100382.

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