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COMPARISON OF QUANTUM DEEP LEARNING METHODS FOR IMAGE CLASSIFICATION

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Keywords
Quantum Transfer Learning, Quantum Artificial Intelligence Models, Hybrid Quantum-Classical Learning, Vision Transformers.

Abstract

Nowadays, with the discovery of the power and potential of quantum computers, developing and understanding quantum-based deep learning models has become an important research area. This study investigates Quantum Transfer Learning and Quantum Hybrid Learning models that involve feature extraction and training processes using Convolutional Neural Networks (CNN) and Vision Transformer (ViT). The study aims to explore the potential advantages and differences of quantum deep learning techniques. It is envisioned that quantum computing can provide significant advantages in terms of computational speed and efficiency, especially in complex and large-scale data sets. Therefore, this study will contribute to a better understanding of the practical applications and potential impacts of quantum deep learning techniques. In this study, we evaluate the performance of four different quantum deep learning architectures using two different datasets. The classifiers used are the pre-trained ResNet-50 with a kernel size of 5x5 and the state-of-the-art CaiT-24-XXS-224 (CaiT) transducers. Optimization was performed with Adam optimizer using the cross entropy loss function. A total of eight models were trained, each with ten iterations. Accuracy (Acc), balanced accuracy (BA), overall $F\beta$ (F_beta) macro score F1 and F2, Matthew's Correlation Coefficient (MCC), sensitivity (Sens) and specificity (Spec) were used as performance measures.

GÖRÜNTÜ SINIFLANDIRMADA KUANTUM DERİN ÖĞRENME YÖNTEMLERİNİN KARŞILAŞTIRILMASI

Anahtar Kelimeler
Kuantum Transfer Öğrenme, Kuantum Yapay Zeka Modelleri, Hibrit Kuantum-Klasik Öğrenme, Vision Transformers.

Öz

Günümüzde kuantum bilgisayarların gücü ve potansiyelinin keşfedilmesiyle birlikte, kuantum tabanlı derin öğrenme modelleri geliştirmek ve anlamak önemli bir araştırma alanı haline gelmiştir. Bu çalışma, Evrişimli Sinir Ağları (CNN) ve Vision Transformer (ViT) kullanılarak öznitelik çıkarımı ve eğitim süreçlerini içeren Kuantum Transfer Öğrenme ve Kuantum Hibrit Öğrenme modellerini incelemektedir. Çalışma, kuantum derin öğrenme tekniklerinin potansiyel avantajlarını ve farklılıklarını araştırmayı amaçlamaktadır. Kuantum hesaplamanın, özellikle karmaşık ve büyük ölçekli veri setlerinde hesaplama hızı ve verimlilik açısından önemli avantajlar sağlayabileceği öngörülmektedir. Dolayısıyla, bu çalışma, kuantum derin öğrenme tekniklerinin pratik uygulamalarının ve potansiyel etkilerinin daha iyi anlaşılmasına katkıda bulunacaktır. Bu çalışmada, iki farklı veri seti kullanılarak dört farklı kuantum derin öğrenme mimarisinin performansı değerlendirilmiştir. Kullanılan sınıflandırıcılar, önceden eğitilmiş 5x5 çekirdek boyutuna sahip ResNet-50 ve son teknoloji ürünü CaiT-24-XXS-224 (CaiT) dönüştürücüleridir. Optimizasyon, Adam optimizer ile çapraz entropi kayıp fonksiyonu kullanılarak gerçekleştirilmiştir. Her biri on tekrarlı olmak üzere toplam sekiz model eğitimi yapılmıştır. Performans ölçütleri olarak doğruluk (Acc), dengeli doğruluk (BA), genel $F\beta$ makro skorundan F1 ve F2, Matthew's Korelasyon Katsayısı (MCC), duyarlılık (Sens) ve özgüllük (Spec) kullanılmıştır.

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Highlights (At least 3 and maxium 4 sentences)

- Quantum computing offers significant advantages in processing complex and large-scale datasets, making it a powerful tool for accelerating deep learning models.
- Quantum Transfer Learning combined with Vision Transformers (ViT) enhances the extraction of both local and global features, leading to higher accuracy in image classification tasks.
- The hybrid quantum-classical models demonstrate strong performance, particularly on simpler datasets, by integrating quantum gates within classical deep learning architectures.

Purpose and Scope

The paper aims to explore the development and application of quantum-based deep learning models, specifically focusing on Quantum Transfer Learning and Quantum Hybrid Learning techniques. By leveraging Convolutional Neural Networks (CNN) and Vision Transformer (ViT) architectures, the study investigates the potential advantages of quantum deep learning, particularly in terms of computational speed and efficiency when applied to large and complex datasets.

Design/methodology/approach

The study evaluates four different quantum deep learning architectures using two distinct datasets. Feature extraction is performed with pre-trained ResNet-50 and CaiT models. Optimization is carried out using the Adam optimizer and cross-entropy loss function. Eight models are trained, each for ten iterations, with performance measured by metrics like accuracy, balanced accuracy, F1 and F2 scores, Matthew's Correlation Coefficient (MCC), sensitivity, and specificity.

Findings

The study reveals that quantum deep learning models, especially Quantum Transfer Learning, exhibit significant advantages in classification tasks. Models utilizing pre-trained ResNet-50 outperform those with CaiT, particularly on complex datasets like "Dogs & Cats." Hybrid quantum models show high accuracy for simpler datasets (Medical MNIST), demonstrating the potential of quantum models for enhanced image classification.

Research limitations/implications

The research is limited by the current state of quantum computing hardware, particularly the challenges posed by noisy intermediate-scale quantum (NISQ) devices. Future research could explore improving the quantum-classical hybrid models' scalability and performance on larger datasets. More comprehensive experimentation is needed to optimize hyperparameters and training time for complex quantum architectures.

Practical implications

The findings suggest practical applications of quantum deep learning in fields requiring fast and efficient data processing, such as medical imaging and large-scale visual recognition tasks. Quantum Transfer Learning could be further developed for use in industries where quick decision-making and high accuracy are critical.

Social Implications

The impact of this research on society could be profound, especially in improving computational tools in healthcare, AI-driven diagnostics, and other data-intensive fields. By accelerating image classification processes, quantum computing has the potential to reduce computational costs and enhance the quality of life through better AI-powered solutions.

Originality

This paper contributes to the existing knowledge on quantum machine learning by carrying out a cross-comparison of quantum transfer learning and quantum hybrid learning models for image classification purposes. This paper makes an important observation on how effective these models are, highlighting their usefulness beyond mere conceptualization especially in processes that require handling large and complex datasets.

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1. Introduction

There has been a drastic change in the field of computer science and its corresponding applications with the emergence of quantum science, which has the ability to exist over and above conventional computers. Unlike classical charged devices which store information in bits represented by either 0 or 1; quantum computers store information in qubits that can be both 0 and 1 at the same time due to superposition principles of qubits. This offers a real possibility that speed would be improved in the solution of some problem systems if this method is compared with normal computer systems. Due to the complexities in computations associated with quantum computing, there have been growing interests in artificial intelligence and machine learning regarding these technologies (Shor 2002).

Quantum transfer learning and hybrid classical-quantum learning represent methodologies through which researchers endeavor to integrate quantum computing into machine learning. It aims to make use of acquired information from the source task to achieve better results on the target task. Classical and quantum methods are used to solve a complex problem in hybrid classical-quantum learning. Both the above forms have their likely advantages but further studies are needed to understand how they differ and when each of the forms would be more appropriate (Dhara et al. 2024).

The two methods, quantum transfer learning, and hybrid classical-quantum learning mostly differ in respect to being algorithmically complex and in data handling (Liu et al. 2021). Quantum transfer learning usually involves the movement of data and involves the methodologies of choosing the right quantum features. Encoding data and correlating it to the asked question in the case of quantum transfer learning is very essential. However, hybrid classical-quantum learning is a considerable amount of effort to coordinate the classical component, quantum component, and how they work together effectively (Datta et al. 2005).

The fast trends with regards to the machine learning mean that quantum transfer learning and hybrid classical-quantum learning are just beginning points (Yang et al. 2023) Both approaches currently are at a rudimentary stage in terms of relevance and too much is required for them to be translated into solving real problems. It is worth mentioning also the necessity of such approaches but with the emphasis on their merits and demerits in more pragmatic and broader context (Arthur et al. 2022). In their opinion, these methods will become even more effective and widespread with the evolution of powerful and more advanced quantum computers in the near future (Liu et al. 2021).

This research has focused on the principles of quantum transfer learning and hybrid quantum learning using Convolutional Neural Networks (CNN) and Vision Transformers (ViT) as an experimental investigation. The four variations of the quantum deep learning architecture were assessed using two datasets. The other methods discussed were evaluated using parameters of accuracy, balanced accuracy, and Matthew's correlation coefficient. This research seeks to investigate possible benefits and inherent differences of quantum deep learning methods.

2. Literature Survey

The literature includes different types of researches that deal with quantum machine learning and hybrid approaches including the vacuum of well into a variety of disciplines. In particular, the progress of the quantum measurement science contributes a lot to the appreciation of the practical application of quantum transfer learning as well as the hybrid of classical and quantum learning. Consideration of some recent contributions from the literature makes it clear that Yang J. et al. (2023) focused on integrating tunable control parameters in the encoding process to enhance the quantum measurement science and their auto-optimization in the process using a hybrid quantum-classical technique. Usually, the above method leads to an experimental guided optimization of the optimal protocol in order to improve the accuracy of measurement. Young-woo Han (2022) presented the significance of a hybrid quantum-classical neural network architecture, where each of the neuron structures consist of a variational quantum circuit. The constructed hybrid neural network was tested in a series of experiments on binary classification tasks of both computer simulations and real quantum computers and their hybrid versions.

J. Liu et al, (2021) a hybrid quantum-classical convolutional neural networkinspired by the classical convolutional neural networks, or QCCNN, was developed earlier in 2021. QCCNN is designed such that it can fit within the available thresholds for the number of qubits and circuit depth when it comes to today's noisy intermediate-scale quantum computers NISQ. QCCNN is able to retain the main concepts of the classical CNN even while facilitating the process of gradient backpropagation for hybrid quantum-classical loss functions design. The authors

illustrated the prospects of this architecture on Tetris and demonstrated that QCCNN was superior in classification tasks than classical CNN.
Mari A. et al. (2020) touched on the matter of transfer learning, a notion often used in contemporary machine learning algorithms, particularly in the class of hybrid neural networks, combining classical and quantum parts. They suggested different usage scenarios of such hybrid transfer learning, especially constraining on the scenario when the last layers of standard trained classical network are substituted by a quantum circuit. This way, it is possible to efficiently normalize a high-dimensional space and extract and transfer a chosen informative volume to the quantum processor. The authors presented some functioning prototypes of the system for works with image recognition and quantum state classification.

Toğoçar M. (2021) examined application of a Quantum Transfer Learning model for the recognition of respiratory diseases. Respiration-related disease was detected using Quantum Transfer Learning model. A different learning paradigm was suggested by integrating quantum and deep learning models. In respect of the application analysis, the dataset was trained with the proposed model, and the accuracy of the training reached 92.50% based on the analysis results.

Mogalapalli A. and others (2022) studied the topic of classical-quantum transfer learning, more specifically the question on if it is possible to substitute the last classical layer of a network with variational quantum circuit. They proposed quantum transfer learning in order to detect tuberculosis from chest X-ray images as well as to identify the disease in X-ray images of affected patients.

Yan J. and others (2023) investigated the use of a hybrid model in remote sensing image classification. US model combined ResNet based classical CNN's and quantum circuits with the objective of achieving high level of accuracy when only few samples were used. The hybrid CNN approach not only enhanced the accuracy of classification tasks but reduced the amount of training data required for training the model.

Cherrat A. and others (2024) set out to achieve more complicated tasks in their investigations by integrating Vision Transformers classical variants and quantum components within the framework of this study. They applied attention with a quantum cavity and obtained impressive results, particularly in the image classification task. Due to this hybrid model, the accuracy improvement rate was significantly increased while the parameters used were relatively lower than those employed in the classical vision transformer models.

Sarkar S. et al. (2024) ingeniously presented a model of quantum transfer learning that elicits both the classical and quantum modes of information processing and explored it on the MNIST database. In this case, data was processed using quantum circuits and the classification was performed therefore using classical neural networks. Nevertheless, the authors highlighted that due to the present-day constraints of quantum devices, the improvement of the model was inferior to the best classical models.

Quantum Convolutional Neural Networks represent a quantum leap in quantum machine learning by the use of quantum properties, such as entanglement and superposition, in the hierarchical processing of complex information. Cong et al. constructed the framework for a QCNN, with a specific view aimed at solution ground states of quantum many-body physics. This has shown that QCNN can carry out dimensionality reduction and hierarchical learning with great scalability and efficiency while dealing with quantum data. Furthermore, the proposed architecture is coherent with the use of QCNNs for a wide range of other quantum computing tasks that are far from physics.

3. Material and Method

In this section, the foundations of quantum machine learning and deep learning models using these foundations will be examined.

3.1. Quantum Entanglement and Quantum Gates

Quantum entanglement is the state in which two or more qubits are in the same state even if their spin is in a different physical location. This statement highlights the extent of the correlation since if the direction of one qubit is measured, the directions of the other qubits are instantly known regardless of distance. When working with qubits within quantum computers & quantum supervised learning systems, statistics of qubits are made computationally powerful with the use of entanglement. Usually, qubits are optimally entangled utilizing a CNOT gate and a Hadamard gate. The Hadamard gate transforms the qubit into a superposition while the CNOT gate links this qubit to another spin. Lastly, these gates combined produce a powerful quantum entanglement in states which leads to improvements in these models' quantum computing power (Wang and Yang, 2020).

The Hadamard gate is one of the key components of quantum computers since it converts classical bits having values of either zero or one into quantum bits in superposition. It works on a single qubit where it takes a yes/might state and places it into an even weighted distribution of both $|0\rangle$ and $|1\rangle$. As a result, in measurement, there is a 50% probability that the qubit is in either state. This gate is the building block of many quantum gates furthering the efficiency of various quantum algorithms and more so making superpositions. For instance, its use is key in the quantum Fourier transform and the Deutsch-Jozsa algorithm. The Hadamard gate is instrumental in enhancing the parallel processing capabilities of quantum transfer learning models by placing each qubit into superposition (Smith & Doe, 2019).

The RY gate, as its name indicates, performs a rotation of the qubits around the y-axis of the Bloch sphere where in this case the angle can be set to any desired value. It has an angle of rotation whose value is adjustable, hence this allows continuum deformation in the model by having learnable parameters. The RY gate is critical in quantum transfer learning models as it enables the effective adjustment of qubit states and aids the convergence of the optimization process. It has similar functions to weight updates as seen in classical ML models. Rotating each qubit around the y-axis would help in searching for each individual state in order to enhance the learning capacity of the model (Lee & Kim, 2020).

The CNOT gate is one of the simplest quantum gates that helps to create an entanglement between the two qubits. In this gate one qubit's control modifies the other qubit's state. The dynamics are that if the control qubit is in the $|1\rangle$ state, the target qubit's state will be flipped and if the control qubit is in the $|0\rangle$ state, the target qubit will not be affected. Such mechanism allows for the engagement of the two qubits in quantum entanglement a crucial aspect of quantum computing where parallel computation that is impossible with classical computers can be performed. This feature of quantum systems is very useful for increasing the effectiveness of quantum transfer learning models. This increases the processing efficiency of the qubits' connectivity in multi-qubit systems (Patel & Sharma, 2021).

3.2. Quantum Machine Learning

Quantum machine learning is a relatively new field of research which gives considerable hope to overcome the weaknesses of classical machine learning systems and to address more computationally intensive tasks. Apart from these, quantum support vector machines (QSVM) fall into one of the important applications of quantum machine learning. QSVM is the version of the classical Support Vector Machines (SVM) algorithm that has been modified for use with quantum computers. In other words, it is an implementation of SVM with the help of quantum approaches such as quantum superposition and quantum parallelism. Examples of these datasets include those utilized in our earlier work in SVM applications and QSVM outperformed predictions. So working QSVM advances research in the field of quantum machine learning which aims at improving classification methods (Cross, 2018).

3.3. Quantum Support Vector Machines

Support Vector Machines (SVM), in short SVM, is a machine learning method that is supervised in nature and is used mostly to address the machine learning problems which can be separated linearly. The purpose of the SVM 's is to find a hyperplane that segregates multiple category feature vectors. This hyperplane is the decision border that distinguishes the classes with respect to given data. SVM aims towards pushing the boundary to the maximum supporting margin where the support vectors are the nearest points to the hyperplane. Based on the kernel used by SVM algorithm the objective function is sometimes convex and at times non-convex. In real applications, non-convex functions lead to dropping down to local solutions where these limits the traditional SVMs optimization efficiency, accuracy, and speed. Quantum Support Vector Machines (QSVM) makes use of grovers algorithm as a subroutine to make sure that the non-convex cost functions are optimized globally. The quantum SVM algorithm can be described as follows (DiVincenzo, 1998):

$$\theta^T x - c = \pm 1.$$

Here c is constant, x and θ are vectors. It has been anticipated that if θ is optimized, one could rely on the margin value whence a correct classification of the data is achieved. Thisintention is formalised by the following optimization problem (Noble, 2006) and constraint (Romero et al., 2017):

$$\min_{\theta,c} \frac{1}{2} ||\theta||^2$$

$$y^i(\theta^T x^{(i)} - c) \geq 1$$

For the training data where i = {1, ..., M} and y(i) = {-1, 1} he constraint can be incorporated into the objective function using Lagrange multipliers α(i) and the optimization problem can be redefined as follows (Khoshaman et al., 2018):

$$\min_{\theta,c} \max_{\alpha^{(i)}\geq 0} (\frac{1}{2} ||\theta||^2 - \sum_{i=1}^{M} [\alpha^{(i)}(\theta^T x^{(i)} - c - 1]$$

An important point is that non-zero values of α(i) correspond to the sum of the support vectors x(i). The following derivatives are set to zero to maximize the objective function F with respect to α(i) (Cong vd. 2019)

$$\frac{\partial F}{\partial \theta^{(i)}} = \theta^{(i)} - \alpha^{(i)} y^{(i)} x^{(i)} = 0$$

$$\frac{\partial F}{\partial c} = \sum_{i=1}^{M} \alpha^{(i)} y^{(i)} = 0$$

Therefore, the weights are defined as (Kerenidis et al., 2019):

$$\theta = \sum_{i=1}^{M} \alpha^{(i)} y^{(i)} x^{(i)}$$

The dual problem is expressed as follows (Henderson et al., 2020):

$$\min_{\alpha^{(i)}} \left\{ \frac{1}{2} \sum_{i,j} \alpha^{(j)} y^{(i)} y^{(j)} \left(x^{(i)}\right)^T x^{(j)} - \sum_{i=1}^{M} \alpha^{(i)} \right\}$$

Under the assumption α(i) ≥ the following equality holds for the training set where i = 1, ..., M:(Farhi vd. 2014)

$$\sum_{i=1}^{M} \alpha^{(i)} y^{(i)} = 0$$

To introduce non-linear effects into the optimization problem, all kernel functions can be expanded with K(x(i), x(j)) replacing the dot product in the dual problem (Schumacher, 1995):

$$\min_{\alpha^{(i)}} \left\{ \frac{1}{2} \sum_{i,j} \alpha^{(i)} \alpha^{(j)} y^{(i)} y^{(j)} K\left(x^{(i)}, x^{(j)}\right) - \sum_{i=1}^{M} \alpha^{(i)} \right\}$$

The Gaussian kernel function is defined as follows (Berenco et al., 1995):

$$K\left(x^{(i)}, x^{(j)}\right) = \exp\left(-\gamma \left\| x^{(i)} - x^{(j)} \right\|^2\right)$$

This requires additional Euclidean distance calculations. Each step of the algorithm is detailed as follows (Toffoli, 1980):

1. Assign initial values for each parameter used by the kernel function.
2. Select an appropriate kernel function for the problem and construct the kernel matrix accordingly.
3. Decompose the objective function and encode its components into qubits. Binary strings can be used to represent classical data (Fredkin & Toffoli, 1982):

$$x \rightarrow b = (b_1, b_2, \dots, b_m)^T$$

Where i = 1, ..., m for b_i = {0, 1} These binary strings can then be easily transformed into k-qubit quantum states (Kockum, 2014):

$$|b_1, b_2, \dots, b_m >$$

This creates a 2^k-dimensional Hilbert space spanned by {|00...0>, |10...0>, ..., |11...1>} (Rebentrost, 2014).

The quantum minimization program searches the space where the objective function is defined. Grover's algorithm searches through the space of all possible objective function values to find the optimal α(i) values corresponding to the solution for θ and c. First, a quantum circuit representing the objective function, using a quantum operator denoted as "O," generates a superposition of all possible inputs. This process allows for the global minimum of the SVM optimization problem to be reached. Measuring this subroutine yields the correct answer with high probability. Grover's approach reduces the temporal complexity of the classical algorithm, which is O(N) to O(√N) where N is the number of training vectors, enabling the discovery of a global minimum. Calculating the kernel matrix is one of the most time-consuming steps in any SVM algorithm, with a computational complexity of O(M^2N). Grover's approach remains subject to the same constraints as the GroverOptim quantum subroutine. Due to quantum noise, ideal results may not always be achieved. It is assumed that the objective function of the SVM is represented by a quantum circuit as input to the algorithm (Zhu et al.).

3.4. Quantum Classification Models

In this work, a hybrid quantum model was built by interposing quantum gates from the Qiskit library among the deep learning layers in pytorch (Qiskit, 2022).

3.4.1. Hybrid Quantum-Classical Learning

The open-source PyTorch library contains numerous modules related to deep learning. In this study, a Hybrid Quantum Model is created by incorporating quantum gates from the Qiskit library into the deep learning layers within PyTorch.

Figure 1, circuit of hybrid quantum-classical learning model. It consists of ZZFeatureMap for the conversion of classical data points to quantum states, and RealAmplitudes as a parametric quantum circuit. While ZZFeatureMap provides the basis for quantum operations by encoding the data points into the quantum feature space, the RealAmplitudes circuit will optimize the learning process using entanglement and rotation gates. It allows both quantum and classical parts to cooperate and enhances performance through this means. This is one of the approaches of the hybrid model, where it tries to scale up data processing capabilities through the combined workability of classical and quantum methods. (Cerezo et al., 2021).

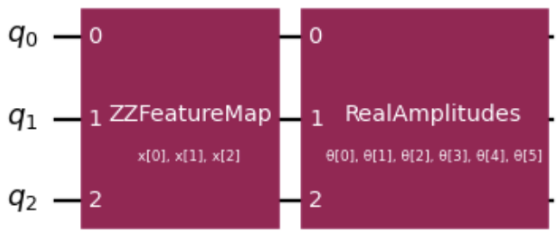


Figure 1. Hybrid quantum-classical learning quantum circuit

To construct a quantum-classical neural network, a hidden quantum layer can be formed within the neural network by utilizing a parameterized quantum circuit. As shown in Figure 2, the neural network begins with classical neural nodes, and the outputs from these layers are used as inputs for the parameterized quantum circuit. The measurement outputs of the quantum circuit are then connected to a classical neural network to form the overall neural network structure (Mari et al., 2020).

Here, σ represents a nonlinear activation function. The value of hi represents the output of the i-th neuron in each hidden layer. R(hi) refers to the quantum rotational gate applied based on the value of hi. The output produced by the hybrid neural network is denoted by y. In the backpropagation algorithm, the parameters of the quantum layer are calculated using the function shown in Figure 2 (Garg and Ramakrishnan, 2020).

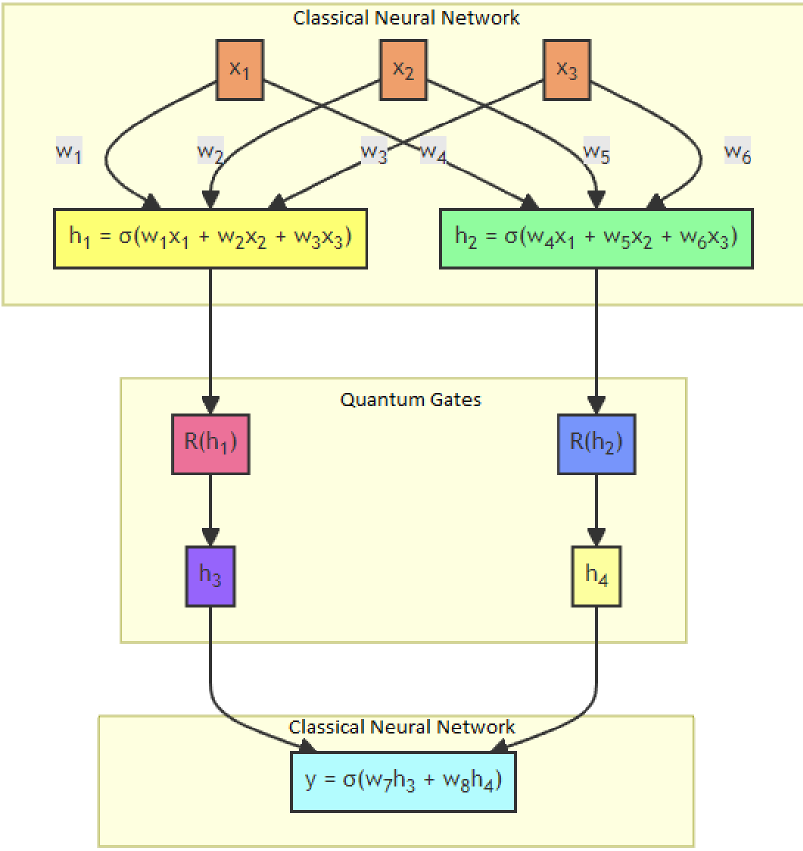
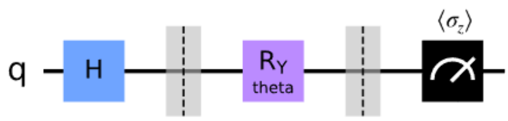


Figure 2. Garg and Ramakrishnan 2020

$$\nabla_\theta Quantum\ Cicuit\ (\theta) = Quantum\ Circuit\ (\theta + s) - Quantum\ Circuit\ (\theta - s)$$

In quantum backpropagation, θ represents the parameters of the quantum circuit. The shifts in the backpropagation are represented by s. The gradient computation in the quantum circuit is simply calculated using the difference between θ + s and θ - s. This function is also known as the parameter-shift rule (Banchi & Crooks, 2021). In the quantum function within the hidden layer, a simple approach uses a single qubit. To determine the θ angle at the output of the circuit, the RY(θ) function shown in Figure 3 is employed (Salinas et al.).



$$\sigma_{\mathbf{z}} = \sum_i z_i p(z_i)$$

Figure 3. Quantum circuit and RY(θ) function (Shepherd 2006)

In the case of the presence of a quantum layer, the classical neural network should satisfy dimensionality requirements with the quantum layer. In the given example, since quantum layer comprises one single qubit, the connections between the classical neural networks and the quantum layer have to be limited to one dimension (Shepherd, 2006).

3.4.2. Quantum Transfer Learning

Quantum transfer learning involves the classical computer basing its computation on ones previously learnt by the quantum computer. This makes it possible for classical as well as quantum computers to quickly and accurately assimilate information already internalized by classical computers. (Mari et al. 2020) The significance and utilization of quantum machine learning algorithms necessitate quantum transfer learning. For instance, because of computers' unique speed advancement when compared to classical computers, there is scope of improving the learning of quantum computers through the application of the learned features of classical computers. (Liu et al. 2021)

Yhis quantum transfer learning technology extends the application of quantum algorithms in an effort to leverage classical algorithm's learned datasets. In this manner, the time associated with the algorithms of quantum science is curbed while its accuracy and success levels can burgeon. These aspects have led to the prospect of solving concrete problems with the help of quantum transfer learning technologies, for instance quantum computers can be used to train classical neural networks, so that it would be possible to build quantum neural networks in the future. (Mari et al. 2020)

Owing to the feature that quantum computer resources can be expanded, it would also be possible to do machine learning applications such as classification or regression on bigger and more complex data. Even classically captured images can be recognized with the help of quantum transfer learning together with the application of quantum algorithms enhancing classical algorithms towards achieving work such as image, speech, and language recognition. (Qi and Tejedor 2022)

Another potential area for utilizing quantum transfer learning is to enable quantum computation techniques, such as quantum control or quantum optimization, aided by computational models or data developed using classical computation techniques. This will enhance the performance of quantum computers since they will be aided by embedded classical computing knowledge. (Mari et al. 2020)

It helps quantum computers increase their learning speed and accuracy towards the models or datasets achieved by classical computing. This is the reason why it is possible to deploy quantum computers with great efficiency in practical applications even for the tasks that are certainly not permissible or would be extremely hard for conventional computers.

In the quantum transfer model, a quantum circuit is implemented on the solution of a general problem obtained with classical neural networks in order to address various subproblems of the same type. In most cases, instead of training a problem from scratch, a pre-trained network in a similar domain can be used. By replacing the last layers of the pre-trained network with quantum layers and optimising them, the solution of a different problem can be approached.

In general, the transfer learning process can be described as follows: A' network is obtained by removing the last few layers from a trained neural network called A. To this network, an untrained neural network called B is added. Using the new data set, the A'+B neural network is retrained and the training process is completed. Figure 4 shows four different approaches of the transfer learning process. (PennyLane 2022)

As shown in Figure 5, the Quantum Transfer Learning model has an input layer that starts with Hadamard (H) gates that bring quantum bits (qubits) into a superposition state. Then, using RY gates, each qubit is incorporated into the learning process with parameterized rotations. In the entanglement layer, CNOT gates increase the quantum computing capacity of the model by creating dependencies between qubits. This process is iterated throughout the depth of the model and finally, measurement operations are used to analyze the qubit states and obtain the results. This structure provides a powerful learning framework by effectively integrating both classical and quantum components.

There are four different transfer learning models. Among these, the classical-to-classical transfer method is already widely used with existing techniques. In the classical-to-quantum transfer method, features selected by leveraging the large-scale data processing advantage of classical models are captured and transferred to quantum circuits for faster processing. This study utilizes the classical-to-quantum transfer method. Another approach, the quantum-to-classical transfer model, involves feeding output data obtained from a pre-trained quantum network as additional input to a new classical neural network. This allows the data to be processed more comprehensively (Mishra and Samanta, 2022).

In the final method, the quantum-to-quantum transfer learning approach, the same technique is applied entirely within a quantum mechanical framework. In this case, a quantum network is pre-trained for a general task and dataset. The final quantum layers from the trained model are removed and replaced with a trainable quantum network optimized for a specific problem. Unlike the previous methods, this process is entirely quantum-based without intermediate measurements, ensuring that features are transferred in a coherent quantum state and that consistent superpositions are maintained. Compared to classical computers, current NISQ (Noisy Intermediate-Scale Quantum) devices are not only noisy and small but also relatively slow. Training a quantum circuit can take a long time as each optimization step (e.g., calculating the gradient) requires numerous measurements (i.e., performing many real quantum experiments). Therefore, approaches like quantum-to-quantum transfer learning, which can reduce the overall training time, can be highly beneficial (Mishra and Samanta, 2022).

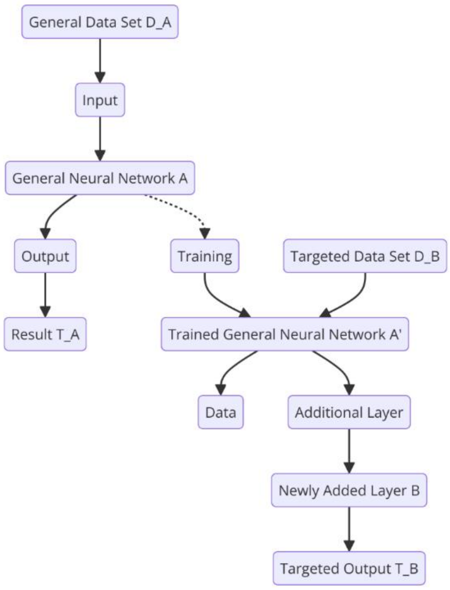


Figure 4. Quatum transfer learning steps (PennyLane 2022)

ResNet-50 is a convolutional neural network characterized by its multilayer structure and good performance in feature extraction. The Quantum Transfer Learning (QTL) model utilizes the pre-trained layers of ResNet-50 to efficiently extract complex features and incorporate them into the quantum learning process. ResNet-50 is a model with a high generalization capacity that yields very successful results, especially on simpler datasets such as Medical MNIST. Therefore, ResNet-50 was chosen as a core component for the QTL model. This choice also reflects the layered structure of ResNet-50 and the potential of the pre-trained network to work harmoniously with various quantum gates.

3.5. Vision Transformers

The Vision Transformer (ViT) is a Transformer model designed for computer vision. ViT divides an input image into a series of patches (similar to tokens in text), converts each patch into a vector, and maps them to a lower-dimensional representation using a single matrix multiplication. These vector representations are processed by a Transformer encoder, similar to token representations (Dosovitskiy et al., 2021). ViT has been used in various computer vision applications such as image recognition, image segmentation, and autonomous driving (Khan et al., 2022).

ViTs emerged from pioneering efforts to apply Transformer-like architectures in computer vision (CV), inspired by the success of Transformers in natural language processing (NLP). These models have proven effective across three key CV tasks (classification, object detection, and segmentation) and with various sensory data types (images, point clouds, and visual-linguistic data). Because of the robust modeling hands-on experience, ViTs have been able to significantly outbeat the performance metrics of several modern convolutional neural networks (Han et al., 2022)

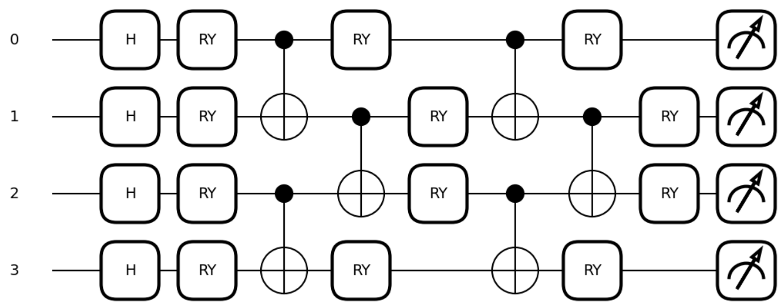


Figure 5. Quantum transfer learning entanglement circuit

3.5.1. Basic Operation Steps of Vision Transformers

The image deploys an image patch of size P x P and descends towards enabling the image size to be H x W offering a total of (HW) / (PP). Each P patch is flattened into a vector of size D. Each P P C patch is linearized into D via a linear transformation i.e. fully connected layers. Each patch vector is then augmented with a D-dimensional encoding vector which represents the position of the respective patch thereby assisting the model on the ordering of the patches. The embedded vectors are progressively processed through layers of Transformer blocks, which consist of multi-head self-attention and feedforward networks. Inputting the output from the last Transformer block into the classification layer helps the system to predict the class of the image i.e. (Steiner et al. 2021). Figure 6 shows a simple vision transformer model graph. This is due to the fact that Vision Transformers (ViT) possess highly efficient abilities in visual feature extraction. The absence of local bias in the image helps to Mness on Peters architecture as it is imaging image thermal management systems imaging heat processes more efficiently within the framework of ViTs. medial cortical The broader context imagery comprehension processes and performance degradation in the more complex visual tasks.

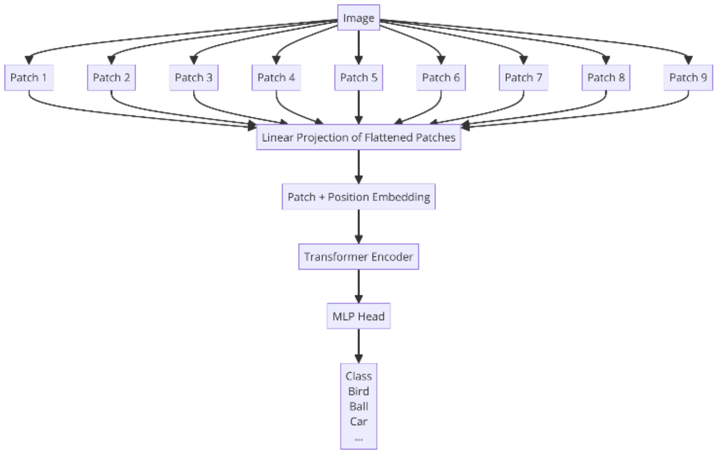


Figure 6. Vision transformer model (Dosovitskiy 2020)

3.5.2. Using Vision Transformers with Different Models

Vision Transformers (ViT) shows great means of handling image feature extraction. The way images are presented is changing as ViTs improve the way of extracting global features of the images by employing a Transformer structure which, and replaces conventional convolutional neural networks (CNNs). This is vital in the comprehension of the larger aspects of images and helps in performing more difficult image-related activities.
ViTs split an image into several fixed-size patches and assign a vector to each patch. These vectors are fed into Transformer blocks and thus the model is able to learn the local and the global features. This way, ViTs possess the ability to retrieve high-level targeted features from the visual images. These features are applicable for the performance of different visual tasks like image classification, object detection, and segmentation which makes ViTs an effective component in Image analysis and computer vision Carion et al., 2020).

3.5.3. Combination of Vision Transformer and Quantum Models

In the case of working with images, where the ViTs are used to extract features, Quantum Transfer Learning can apply these features to construct quantum states and processes. Let this be the first step. ViT will take the image and cut it into smaller fixed-size images and Patches will be transformed into vectors. These vectors are then advanced forward through the Transformer blocks and the model now learns the local and global features. These features are then used to feed into the Quantum Transfer Learning model by Liu et al., 2021.Related Work and Technology.

In the Quantum Transfer Learning model, Hadamard gates are applied to every qubit with the H_layer function. After this, the function RY_layer is used for parameterized rotations on every qubit, which are dependent on the features extracted by ViT. The next step is a succession of trainable variational layers. In each layer, the function entangling_layer is first used to implement CNOT gates, followed by the use of the function RY_layer, which totally changes the picture, depending on model parameters.

The last step is the calculation of the expected values for a Z-Basis for every qubit of which qubits are the output. These are the final outputs of the Quantum Transfer Learning model, which are passed through a classification layer, where the class of the image is determined based on the outputs (Liu et al, 2021).

This method enables the involvement of the efficient feature extraction provided by ViT in the modelling of complex quantum features with the aid of quantum transfer learning. It can be beneficial in the performance of more advanced quantum tasks. Nonetheless, more work is needed since many questions still remain unsolved in this scope.

The CaiT model, with its Transformer-based architecture, is a particularly prominent approach for effectively extracting both local and global features. When combined with QTL, CaiT increases the capacity to extract meaningful information from multidimensional and complex visual datasets. This model has been particularly favored for more complex datasets such as Dogs & Cats. CaiT's ability to operate with low local bias is an important contribution to quantum transfer learning models. This choice is based on the potential of CaiT's feature extraction capabilities to create ideal inputs for quantum computations.

In this respect, therefore, the current state-of-the-art in quantum machine learning is beset by several major challenges, not least of which concern NISQ devices. Such devices are characterized by small numbers of qubits, high levels of noise, and shallow circuit depths—all factors that severely limit their complex computational capability. Equally, many quantum models prove incapable of outperforming their classical versions due to hardware constraints; that limits any effort to isolate what is peculiarly advantageous in the quantum processing. These constraints notwithstanding, hybrid quantum-classical approaches have already become an auspicious avenue through which one can try to exploit the strengths of the two paradigms while mitigating their respective individual limitations. (Benedetti et al., 2019).

Given these challenges, this work leverages a hybrid quantum-classical framework wherein the classical part does the heavy lifting, including most of the computations that are required in feature extraction and early processing. The models of ResNet-50 and CaiT can be used because they have great strength in the derivation of meaningful features, especially from simpler datasets such as Dogs & Cats and Medical MNIST. These datasets provide an accessible starting point to evaluate hybrid quantum-classical models under manageable conditions (LeCun et al., 1998).

However, the quantum part is not strong enough to replace the classical one. Instead, it can only act like a complementary feature that introduces special operations native to quantum systems, such as entanglement and superposition, which help improve the learning process by projecting classical features into higher-dimensional feature spaces. This enables the hybrid model to learn nonlinear relationships present in the data that might not have been captured by purely classical models. These various performance improvements illustrate that even for NISQ devices—small number of qubits, high levels of noise, shallow circuit depths—quantum processing adds value to a classical learning framework (Cerezo et al., 2021).

Also, the comparative results suggested that the hybrid model outperforms the classical pure systems, thus suggesting that the contribution coming from the quantum part is supplementary but brings meaningful advantages regarding image classification tasks. To conclude, these constitute a potential number of quantum processing as an enhancement, especially in hybrid systems where the foundation is in classical processing and quantum operations open up new dimensions for feature learning. (Schuld et al., 2019)

3.6. Limitations of NISQ Devices and Their Impact on Experimental Results

Operations of NISQ devices consist of quantum rounds, and owing to the finite qubit capacity of these devices available, there will be errors in the computation steps. The levels of noise and numerical error rates can also hinder the effective functioning of quantum circuits and as a result, the performance of the model erodes over time. This problem aggravates in the models who are basing their working with deep quantum circuits, narrowing down the generalization ability of the model. (Preskill 2018)

Scaling complex models becomes difficult on such devices due to the limited number of qubits. Execution of quantum algorithms that necessitate a deeper circuit, or rely on an adequate number of qubits are put on halt and also numerous errors gets accumulated on this systems. Therefore these hybrid classical-quantum models should be built for less complicated problems. (Bharti et al. 2022)

When it comes to the processes of optimization of quantum algorithms, it is more difficult than classical algorithms. In particular for hybrid models, there exist progressive associated with time, noiseless computations of the quantum circuits optimization parameters. This happens and makes the quantum modeling for tough tasks developed a bit unreasonable and makes them operational without the NISQ device's restrictions. (Cerezo et al. 2021)

Performing quantum circuits on these systems requires a lot of time. This is because of the requirement to take several measurements as a single step, which makes the optimization processes to take longer in duration thus elongating the training period and adversely affecting the reproducibility and precision in conducting the experiments. (McClean et al. 2020)

NISQ devices presently have some considerable drawbacks, even as they promise a great deal for quantum computing. Whereas they are good at demonstrating exponential computational capabilities because of quantum properties such as entanglement and superposition, they do this at low precision because of the high noise figure and lack of error correction mechanisms on their circuits. Current NISQ devices are usually limited by small numbers of qubits, which in turn reduce the possibility for more complex and deep circuits. This typically comes in the form of cloud access, and users also have access for fixed numbers of hours. The multiple limitations of NISQ because the testing of hybrid quantum models by Buscemi et al. are done in a simulated environment. The good agreements found in the results clearly show that at lower noise levels with more qubits, real NISQ devices hold better potential in the long term.

3.7. Dataset

The classification datasets were obtained from Kaggle site and were further explored. The first one, Medical MNIST, is made up of 64x64 pixel images depicting X-ray abdominal, hand, chest, head and spine images. This consists of 10,000 images for each class making a total of 50,000 images in all. The medical MNIST data set includes imaging information from the patient's medical records and the hospital's reports (Kaggle, 2017). The second dataset is the one titled 'Dogs & Cats' which consists of around 30000 of cat and dog images with resolution 512 x 512 pixels (Kaggle 2018).

4. Findings

In this section, the results of three different models are compared and explained.

4.1. Training and Test Accuracy Rates

In all the models in this work, the Adam optimization algorithm is employed due to its power of achieving fast convergence by adaptively changing the learning rate. Cross-entropy loss is used herein since it minimizes classification errors and is one of the most used losses in any machine learning task. ResNet-50 and CaiT were fine-tuned using their default parameters. While the pre-trained features were utilized in the quantum framework of the hybrid quantum model, the full development of quantum-specific operations such as entanglement and superposition were further used in this model to enhance its learning process. The best performance, when QTL with ResNet-50 is applied to the Dogs & Cats dataset, can hence be attributed to contributions from classical pre-training and quantum processing. Importantly, the quantum part introduces special types of transformations in the feature space that are altogether beyond the reach of classical methods of optimization.

The accuracy values corresponding to the model and application for the training and test sets are presented in Table 1. In the Quantum Transfer Learning (QTL) model, it was observed that the highest accuracy was achieved by the ResNet-50 pre-trained model during the validation and testing phases. Models pre-trained with CaiT demonstrated optimal performance in the first or second epoch, whereas the ResNet-50 pre-trained model exhibited superior performance in the ninth or tenth epoch. The Qiskit Hybrid Model, given its status as a quantum machine learning model, demonstrated superior performance on relatively simple datasets such as MNIST. The QTL model demonstrated superior performance on the "Dogs & Cats" dataset relative to the MNIST dataset, reflecting its capacity to utilise more sophisticated quantum gates. In contrast, the models based on CaiT exhibited the poorest validation and testing efficiency.

Results of 94.45% training and 95.5% testing accuracy were achieved on the Qiskit Hybrid Model when combined with CNN feature extraction and Dogs & Cats dataset. The Medical MNIST dataset however saw the training and testing accuracy rise to 99.79% and 99.97% respectively. This sheds light on an additional factor regarding the Medical MNIST being an easier dataset, since the model obtains 99.97% test accuracy, at the 8th epoch. With respect to the "Dogs & Cats" dataset, the accuracy of the model was 68.78% at the 10th epoch after which further improvement was expected to be achieved. This means that, possibly, the model can produce better outcomes given the opportunity to extensively train on that dataset.

Table 1. Accuracy values of Qiskit hybrid and QTL models

Model	Feature Extraction	Data Set	Train Acc %	Test Acc %
Qiskit Hybrid	CNN	Cats & Dogs	94.45	95.5
Qiskit Hybrid	CNN	Medical Mnist	99.79	99.97
Qiskit Hybrid	CaiT	Cats & Dogs	69.6	68.79
Qiskit Hybrid	CaiT	Medical Mnist	99.68	99.75
QTL	ResNet (Pre-Trained)	Cats & Dogs	97.38	98.62
QTL	ResNet (Pre-Trained)	Medical Mnist	99.68	99.97
QTL	CaiT (Pre-Trained)	Cats & Dogs	97.75	98.98
QTL	CaiT (Pre-Trained)	Medical Mnist	97.13	98.05

Similarly, the QTL model yielded satisfactory accuracy scores when feature extraction techniques were employed with ResNet and CaiT models. This explains the improvement in performance of the models since they were used in pre-trained models. Even so, it was noted that the feature extraction technique of the ResNet(pre trained) gave better results than that of the CaiT (pre trained). This is likely since the ResNet model has a more elaborate general structure leading to more features being recognized.

4.2. Test Metric Values

In this work, accuracy, F1 and F2 scores, Matthews Correlation Coefficient, and sensitivity/specificity metrics were chosen. These metrics here have been selected as giving a comparison that is complete on the performances of both the classical and quantum models. For example, F1 and F2 scores give sensitivity about models in cases where data are imbalanced. Similarly, the Matthews correlation coefficient gives a balanced measure that takes into account correct and incorrect classifications equally. Sensitivity and specificity are useful for comparing performances across the positive class and the negative class. The fact that it may be so informative, may be because entanglement and superposition-easily seen as unique properties of quantum models-are effective in data classification tasks.

Tables 2 and 3 present the summary of the various metrics that are used to evaluate the different implemented models of artificial intelligence and the performance of the models in the assessment of various features and performance aspects. These metrics serve the purpose of measuring the efficiency of a model, however, bridging the gap of why a model is able to perform well or poorly in most cases is attributed to elements like the type of model, its training, and the type of data used. On the other hand, when CaiT feature extraction was performed and training done on" Dogs & Cats" dataset, the F1, F2, and Fβ scores for Qiskit Hybrid Model were 0.684. While it looks at this point that performance appears to be poor, the situation is more intricate. Again this may be attributed to the fact that no pre-training was done thus it is likely that the CaiT model requires more epochs for training to acquire the relevant features so as to mask the results.

Table 2. Metric values of the Qiskit hybrid model

Model	**Qiskit Hybrid**	**Qiskit Hybrid**	**Qiskit Hybrid**	**Qiskit Hybrid**
Feature Extraction	CNN	CNN	CaiT	Cait
Data Set	Cats & Dogs	Medical Mnist	Cats & Dogs	Medical Mnist
F_1 Score	0.955	0.988875	0.684	0.999
F_2 Score	0.955	0.988875	0.684	0.999
$F_ß$ Score	0.91	0.9775	0.385	0.998
Accuarcy	0.95	0.99	0.68	1.0
Specifity	0.955	0.99	0.69	1.0
Matthew's Sensivity	0.955	0.993	0.7992	0.9985
Macro Avg	0.95	0.99	0.68	1.0
Weighted Avg	0.95	0.99	0.68	1.0

Table 3. Metric values of the QTL model

Model	QTL	QTL	QTL	QTL
Feature Extraction	ResNet Pre-Trained	ResNet Pre-Trained	CaiT Pre-Trained	CaiT Pre-Trained
Data Set	Cats & Dogs	Medical Mnist	Cats & Dogs	Medical Mnist
F_1 Score	0.986	0.9997	0.9898	0.9997
F_2 Score	0.986	0.9997	0.9898	0.9997
$F_{ß}$ Score	0.972	0.9995	0.9796	0.9995
Accuarcy	0.99	1.0	0.99	1.0
Specifity	0.99	1.0	0.99	1.0
Matthew's Sensivity	0.9828	0.99975	09912	0.9995
Macro Avg	0.99	1.0	0.99	1.0
Weighted Avg	0.99	1.0	0.99	1.0

The same parameters as for the above experiment for F1, F2 and Fβ scores were conducted using Qiskit Hybrid Model with CNN feature extraction and "Dogs & Cats" dataset and scores of 0.955 were found. This implies that this model was able to perform very well for the task in hand. But then when the same model was employed with CaiT feature extraction and tested on the same "Dogs & Cats" dataset, the F1, F2 and Fβ values obtained were 0.684 which indicated a drop in performance.

This performance difference may arise from the difference in the feature extraction techniques applied. CNNs are more effective in image classification, however, in this case, CaiT may not be the best approach for the task. This could be cleavage that CaiT has a greater structural complexity and therefore likely to give better results on more complicated datasets.

Nonetheless, when the QTL model was integrated with ResNet-50 (pretrained) feature extraction and employed on the 'Dogs & Cats' dataset, the F1, F2, and Fβ scores were all 0.986 conveying that good performance was quality gained. It is likely that the good performance of this model can be attributed to the use of the pre-trained ResNet-50 model and the QTL model which is appropriate for this sort of task.

5. Result and Discussion

It is apparent from the above sentence that model performance is related to a number of aspects such as the method used for feature extraction, the structure of the model utilized as well as the dataset adopted for model training. Each of these factors can affect the outcomes of the model in a substantial way. It therefore follows that any of these factors has to be analyzed to understand why a particular model works smoothly while another model does not. This may help pinpoint what should be made better in order to improve the efficiency of the model. For example, after extending the training time or changing hyperparameters such a model could demonstrate better performance and therefore promote achieving more precise and better results.

Table 4 contains the best four model results, which embody the outcome from different models and feature extraction techniques on particular datasets. It should be noted that CaiT and QTL models scored very high marks, in line with expectations. ResNet Pre-Trained, CaiT Pre-Trained feature extraction methods reached nearly perfect F1 and F2 scores of 0.9997 and 0.9997 respectively with the QTL model. Similar to the above, Qiskit Hybrid model reached very high F1 and F2 scores of 0.999 with CaiT feature extraction. The QTL model granted nearly the same F1 and F2 scores of 0.9898, but this time on the Cats & Dogs dataset, and used CaiT for feature extraction.

The performance of the models, particularly the CaiT and QTL models, is worth mentioning since they seem to maintain high levels of performance irrespective of datasets used. There is synergy in combining the ability of CaiT to extract features and the QTL model which learns. The QTL model consistently succeeding on a variety of feature extraction methods signifies the best model generalization power. Increasing the dimensions of the simplistically represented data using the convolution based feature extraction improves the performance of the QTL model. The above results demonstrate the feasibility of applying the two approaches in different applications.

The ResNet-50 and CaiT models used in this study exhibited unique capabilities in terms of feature extraction and contributed significantly to the success of the hybrid quantum model. While ResNet-50 provides effective extraction of local and global features with its convolution-based architecture, the CaiT model takes a broader view of the data with its attention-based structure. The performance of the hybrid quantum models was evaluated in a high RAM simulation environment on Google Colab. The simulator used in this study mimics the functionality of NISQ devices. The successful results obtained in the simulation environment indicate that real NISQ devices can perform much better. Therefore, this study highlights the potential of hybrid quantum models and demonstrates that NISQ devices can take this potential to even higher levels.

Taking all things into account it can be observed that there can be great benefits if both CaiT and QTL models are used together, especially in cases which require high precision. Future work could focus on improving this synergy through hyperparameter optimization and training duration. Also, over wider experiments, a attempt may be made to figure out whether the same progress can be made with other datasets.

Table 4. Four best performing models

Model	QTL	QTL	Qiskit Hybrid	QTL
Feature Extraction	ResNet Pre-Trained	CaiT Pre-Trained	CaiT	CaiT
Data Set	Medical Mnist	Medical Mnist	Medical Mnist	Cats & Dogs
F_1 Score	0.9997	0.9997	0.999	0.9898
F_2 Score	0.9997	0.9997	0.999	0.9898
$F_ß$ Score	0.9995	0.9995	0.998	0.9796
Accuarcy	1.0	1.0	1.0	0.99
Specifity	1.0	1.0	1.0	0.99
Matthew's Sensivity	0.9997	0.9995	0.9985	0.9912
Macro Avg	1.0	1.0	1.0	0.99
Weighted Avg	1.0	1.0	1.0	0.99

Conflict of Interest

The authors declare no conflict of interests.

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