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Quantum Machine Learning: The Superhero That Classical Machine Learning Never Knew It Needed

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Abstract
Quantum Machine Learning (QML) is an emerging interdisciplinary field that combines the principles of quantum mechanics and machine learning to develop algorithms that can potentially outperform classical algorithms in certain tasks. QML leverages the unique properties of quantum systems, such as superposition and entanglement, to process information in ways that are not possible with classical computers. This paper provides a comprehensive overview of QML, including its principles, algorithms, and applications. We focus particularly on supervised learning methods, which involve training a quantum model on labeled data to make predictions on new, unseen data. We discuss the potential of QML to revolutionize various domains, such as finance, chemistry, and materials science, and highlight the challenges associated with the development and implementation of QML algorithms, including the need for more advanced quantum hardware and software. This paper aims to provide a clear understanding of the current state of QML research and its potential impact on future computational capabilities.

Keywords: Quantum Machine Learning, Pneumonia Detection, Quantum Convolutional Neural Network (QCNN)

I. INTRODUCTION

The emergence of digital computers in the twentieth century revolutionized the way we process and analyze data. With the rapid progression in computing power, linear algebraic data analysis techniques such as regression and Principal Component Analysis (PCA) became feasible, leading to the development of complex algorithms like the Support Vector Machine (SVM). Alongside the advancement of digital computers, novel machine learning models such as Artificial Neural Networks (ANNs) were implemented in the 1950s. Many Deep Learning Models based on ANNs, like the Hopfield network and the Boltzmann Machines, were also developed, and training via back propagation was implemented. In recent times, by combining powerful computers and particular purpose-intended processors, we have been capable of implementing Deep Neural Networks with billions of weight parameters and extensive data, which have helped identify complex patterns in the data.

Classical novel Machine Learning models like deep neural networks are equipped with the feature of recognizing statistical patterns in the data and producing data that possesses the same statistical patterns. This observation leads to the hope of finding an efficient Quantum algorithm for Machine Learning.

Quantum Machine Learning (QML) software uses Quantum Algorithms as a part of their implementation. The analysis of quantum algorithms shows that they have the potential to outperform their classical counterpart for specific problems, which is termed Quantum Speed-Up. However, the idea of a quantum speedup depends on whether one takes an orderly computer science viewpoint, which necessitates mathematical proofs.

It can also be prospect based on what can be done with realistic, finite size devices, which needs solid statistical evidence of a scaling advantage over some finite range of problem sizes. Resolution of a scaling advantage distinguishing quantum and classical machine-learning would rely on the continuation of a quantum computer. Moreover, it is called a ‘benchmarking’ problem. Such advantages could incorporate refined classification accuracy and sampling of classically inaccessible systems. Subsequently, quantum speedups in machine learning are currently described using idealized measures from complexity theory

- Query complexity
- Gate complexity

Query complexity measures the number of queries to the information source for the classical or quantum algorithm. We say it’s a quantum speedup results when the number of queries needed to solve a problem is lower for the quantum algorithm than for the classical algorithm. Gate Complexity is the number of elementary quantum operations (or gates) needed to obtain the desired result. Query and gate complexity are standardized models that quantify the necessary resources to solve a problem class. Without knowing how to map this idealization to reality, not much can be said about the necessary resource scaling in a real-world scenario. Therefore, the required resources of classical machine learning algorithms are quantified mainly by numerical experimentation. The resource requirements of quantum machine learning algorithms are likely to be similarly challenging to quantify in practice.

II. QUANTUM SPEED-UP

Quantum computers utilize quantum coherence and entanglement to process information in ways that are beyond the capabilities of classical computers. In recent years, there has been a steady advancement in the development of powerful quantum computers.

A quantum algorithm is a systematic method implemented on a quantum computer to solve a specific problem, such as searching a database. Quantum machine learning software employs quantum algorithms to process information. Quantum algorithms have the potential to outperform the best-known classical algorithms in solving particular problems, which is referred to as quantum speedup.

For example, quantum computers can search an unsorted database with N entries in a time proportional to $\sqrt{N}$, whereas a classical computer, given black-box access to the same database, requires time proportional to N. In this case, the quantum computer demonstrates a square-root speedup over the classical computer. Additionally, quantum computers can perform Fourier transforms over N data points, invert sparse $N \times N$ matrices, and find their eigenvalues and eigenvectors in time proportional to a polynomial in log2N. In contrast, the best-known algorithms for classical computers take time proportional to N(log2N), indicating that the quantum computer exhibits an exponential speedup over the best classical computer algorithms.

III. CLASSICAL MACHINE LEARNING

Classical machine learning and data analysis can be classified into certain categories. First, computers can produce ‘classic’ data analysis methods such as least squares regression, polynomial interpolation and data analysis. Machine learning rules can be supervised or unsupervised. In supervised learning, the training data are divided into labelled categories, such as samples of handwritten digits together with the actual number the handwritten digit is supposed to represent, and the job of the machine is to learn how to assign labels to data outside the training set. In unsupervised learning, the training set is unlabeled, and the goal of the machine is to find the natural categories into which the training data falls (for example, different types of photos on the internet) and then categorize data outside the training set. Finally, there are machine-learning tasks that involve combinations of supervised and unsupervised learning, together with training sets that maybe generated by the machine itself.

IV. LINEAR-ALGEBRA-BASED QUANTUM MACHINE LEARNING

Quantum mechanics provides a natural framework for performing matrix operations on high-dimensional vectors, which is a fundamental aspect of many data analysis and machine learning models. A quantum state of n qubits can be represented as a vector in a 2^n dimensional complex vector space, and quantum gates and measurements can be viewed as matrix operations on this vector. By constructing appropriate matrices and implementing them as transformations on a quantum computer, it is possible to perform operations such

as Fourier transforms, eigenvalue decomposition, and solving linear systems of equations exponentially faster than classical algorithms.

One of the most well-known quantum algorithms for linear algebra is the Harrow, Hassidim, and Lloyd (HHL) algorithm, which provides a quantum speedup for solving linear systems of equations. The original version of the HHL algorithm assumed a well-conditioned matrix that is sparse, but later improvements have relaxed this assumption to include low-rank matrices as well. The HHL algorithm and its variants have been used as subroutines in a variety of quantum machine learning algorithms, such as quantum support vector machines and quantum principal component analysis.

V. QUANTUM SUPPORT VECTOR MACHINES AND KERNEL METHODS

Quantum support vector machines (QSVMs) are a powerful example of quantum machine learning algorithms that can be used for classification tasks. Similar to classical support vector machines, QSVMs aim to find an optimal separating hyper plane between two classes of data in a dataset, such that all training examples of one class are found only on one side of the hyper plane with high probability. However, QSVMs leverage the principles of quantum mechanics to perform this task more efficiently.

The key idea behind QSVMs is to use quantum phase estimation and matrix inversion (the HHL algorithm) to construct the optimal separating hyper plane in a time that is polynomial in logN, where N is the dimension of the matrix required to prepare a quantum version of the hyper plane vector. This is in contrast to classical SVMs, which require a time that is polynomial in N.

One of the earliest QSVM algorithms was developed using a variant of Grover's search for function minimization. This approach requires p√N/s iterations to find s support vectors out of N vectors. However, recent developments in QSVMs have led to the creation of a least-squares QSVM that harnesses the full power of qBLAS subroutines. This new approach allows for more efficient processing of data input from various sources, such as qRAM accessing classical data or a quantum subroutine preparing quantum states.

QSVMs can also be generalized to nonlinear hyper surfaces via kernel functions, just like their classical counterparts. Polynomial and radial basis function kernels are commonly used, as well as another kernel-based method called Gaussian process regression. The use of kernel functions allows QSVMs to be applied to a wide range of classification tasks, including image segmentation and biological data analysis. QSVMs have already been experimentally demonstrated in a nuclear magnetic resonance testbed for handwritten digit recognition tasks. The results show that QSVMs have the potential to outperform classical SVMs in terms of both accuracy and efficiency.

VI. SUPERVISED LEARNING WITH QUANTUM COMPUTERS

Quantum computing and machine learning are two rapidly evolving fields that have the potential to transform the way we process and analyze data. A typology introduced by Aimeur, Brassard, and Gambs distinguishes four approaches to combining quantum computing and machine learning based on whether the data is generated by a quantum (Q) or classical (C) system and whether the information processing device is quantum (Q) or classical (C).

CC

The first approach, CC, refers to classical data being processed classically. This is the conventional approach to machine learning, but in this context, it relates to machine learning based on methods borrowed from quantum information research. An example of this approach is the application of tensor networks, which have been developed for quantum many-body systems, to neural network training.

QC

The second approach, QC, investigates how machine learning can help with quantum computing. For example, when we want to get a comprehensive description of the internal state of a quantum computer from as few measurements as possible, we can use machine learning to analyze the measurement data. Another idea is to learn phase transitions in many-body quantum systems, a fundamental physical problem with applications in the development of quantum computers.

CQ

The third approach, CQ, uses quantum computing to process classical datasets. The datasets consist of observations from classical systems, such as text, images, or time series of macroeconomic variables, which are fed into a quantum computer for analysis. This requires a quantum-classical interface, which is a challenge.

QQ

The fourth approach, QQ, looks at 'quantum data' being processed by a quantum computer. This can have two different meanings. First, the data could be derived from measuring a quantum system in a physical experiment and feeding the values back into a separate quantum processing device. A much more natural setting, however, arises where a quantum computer is first used to simulate the dynamics of a quantum system, and consequently takes the state of the quantum system as an input to a quantum machine learning algorithm executed on the very same device. The advantage of such an approach is that while measuring all information of a quantum state may require a number of measurements that is exponential in the system size, the quantum computer has immediate access to all this information and can produce the result, for example, a yes/no decision, directly—an exponential speedup by design.

VII. PROBLEM STATEMENT

Quantum computing has opened new avenues for machine learning algorithms, offering potential breakthroughs in various application domains. In this study, we investigate the efficacy of Quantum Support Vector Machines (QSVMs) in high-energy physics, particularly in identifying the equation of state (EoS) in relativistic hydrodynamic simulations of heavy ion collisions. Additionally, we explore the performance of Quantum Convolutional Neural Networks (QCNNs) in pneumonia detection using medical imaging. Our comparative analysis sheds light on the strengths and limitations of quantum machine learning approaches in diverse tasks.

QUANTUM SUPPORT VECTOR MACHINE WITH DATA FROM HIGH ENERGY PHYSICS

This research paper presents a comparative analysis of two quantum machine learning approaches, namely Quantum Kernel Support Vector Machines (QKSVM), Neural Network and Variational Quantum Circuits (VQC), applied to the task of Equation of State (EoS) metering in Quantum Chromodynamics (QCD). The EoS of primordial matter formed in high-energy heavy-ion collisions is crucial for understanding the nature of the phase transition in QCD. We explore the effectiveness of QKSVM and VQC in deciphering the EoS using supervised learning techniques.

The study of the Equation of State (EoS) in Quantum Chromodynamics (QCD) is essential for comprehending the properties of primordial matter generated in high-energy heavy-ion collisions. Traditional methods for EoS determination rely on relativistic hydrodynamic simulations, which can be computationally intensive and model-dependent. In this paper, we investigate the application of quantum machine learning techniques, specifically QKSVM and VQC, as model-independent and efficient alternatives for EoS metering.

A) Methods:

We commence by elucidating the construction of our dataset, which encapsulates high-level correlations of particle spectra derived from relativistic hydrodynamic simulations of heavy-ion collisions. Preprocessing steps involve feature extraction, wherein we identify salient features relevant to EoS characterization. Subsequently, the dataset is partitioned into training and testing subsets to facilitate model evaluation.

	0	1	2	3	4	5	6
0	0	0.0	0.493280	119.32780	0.026617	0.019539	0.001285
1	1	0.0	0.499796	140.66150	0.027218	0.015303	0.017385
2	2	0.0	0.503392	152.76870	0.011552	0.016412	0.004306
3	3	0.0	0.488244	123.84110	0.016648	0.007232	0.004221
4	4	0.0	0.496821	130.78380	0.029870	0.034460	0.016352
...	...	...	...	...	...	...	...
22570	22570	1.0	0.495708	43.28272	0.031320	0.010866	0.007185
22571	22571	1.0	0.536097	35.77644	0.089789	0.015850	0.006881
22572	22572	1.0	0.516989	40.66633	0.056547	0.031709	0.012869
22573	22573	1.0	0.514398	48.36263	0.059926	0.013307	0.006346
22574	22574	1.0	0.523754	58.44409	0.051211	0.039774	0.009579

22575 rows × 87 columns

Fig. QCD DATASET

B) Approaches Used

i) *Quantum Kernel Approach*:

Quantum Kernel Support Vector Machines (QKSVM) leverage the principles of quantum mechanics to compute a kernel matrix, which is a measure of similarity between pairs of data points in a high-dimensional space. In this approach, the kernel matrix is calculated using a quantum device, typically by preparing quantum states corresponding to the input data and measuring their overlap. QKSVM essentially transforms the classical data into a quantum state representation, where the computation of the kernel function is inherently quantum mechanical. The resulting kernel matrix is then utilized in a classical SVM framework for classification tasks, providing a quantum-enhanced way of analyzing and classifying data. The quantum kernel matrix is computed using a quantum device, typically by preparing quantum states corresponding to the input data and measuring their overlap. This process transforms classical data into a quantum state representation, enabling quantum-enhanced analysis and classification. The resulting kernel matrix is integrated into a classical SVM framework for training. This involves optimizing the SVM parameters to maximize the margin between different classes while minimizing classification errors.

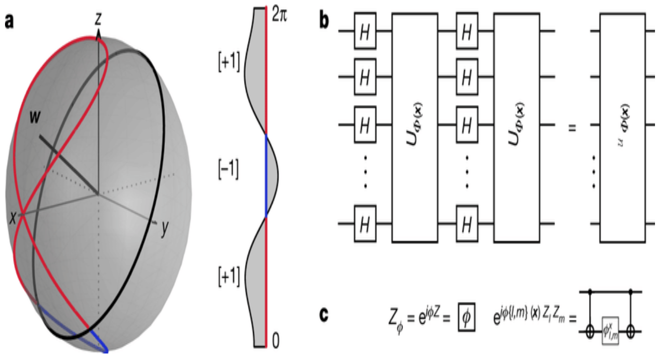


Fig. Quantum Kernel

ii) Variational Circuit Approach

Variational Quantum Circuits (VQC) are parameterized quantum circuits that serve as trainable models for quantum machine learning tasks. In VQC, the parameters of the quantum circuit are optimized to minimize a cost function, typically through gradient-based optimization methods. The variational circuit is designed to encode information about the input data, and the optimization process tunes the parameters to best represent the desired output. VQC can be trained using classical optimization techniques or by utilizing quantum-classical hybrid optimization algorithms. The output of the variational circuit can be interpreted as the prediction or classification result, making it suitable for a wide range of quantum machine learning tasks. The variational circuit is constructed to encode information about the input data, with parameters representing the weights of quantum gates within the circuit. The parameters of the variational circuit are optimized to minimize a cost function, typically through gradient-based optimization methods. This optimization process tunes the circuit parameters to best represent the desired output, making it suitable for a wide range of quantum machine learning tasks. Using the variational principle of training, we can propose an ansatz for the variational circuit and train it directly. By increasing the number of layers of the ansatz, its expressivity increases. Depending on the ansatz, we may only search through a subspace of all measurements for the best candidate.

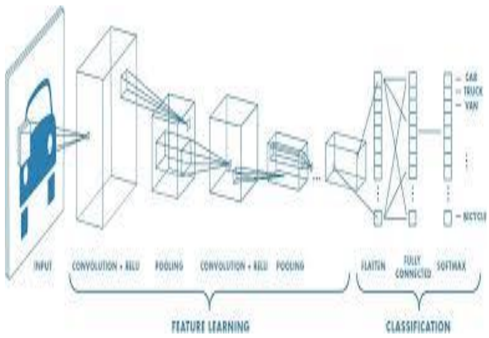
Remember from above, the variational training does not optimize exactly the same cost as the SVM, but we try to match them as closely as possible. For this we use a bias term in the quantum model, and train on the hinge loss. We also explicitly use the parameter-shift differentiation method in the quantum node, since this is a method which works on hardware as well. While diff_method='backprop' or diff_method='adjoint' would reduce the number of circuit evaluations significantly, they are based on tricks that are only suitable for simulators, and can therefore not scale to more than a few dozen qubits.

In the variational quantum circuit, two distinct methods for parameter scaling are employed: linear parameter scaling and square root parameter scaling. In the linear parameter scaling approach, the number of trainable parameters in the circuit grows proportionally with the size of the dataset. This means that as the dataset expands, the number of parameters in the circuit increases steadily, with each data point contributing equally to the overall complexity. Conversely, square root parameter scaling involves scaling the number of trainable parameters with the square root of the dataset size. This results in a more gradual increase in circuit complexity as the dataset grows larger, striking a balance between computational efficiency and model complexity. While linear parameter scaling offers simplicity and predictability, square root parameter scaling provides improved scalability and computational efficiency, making it well-suited for handling larger datasets. By leveraging both methods, researchers can explore various trade-offs between circuit complexity and dataset size, allowing for a more nuanced understanding of the circuit's performance across different scales.

PNEUMONIA DETECTION

Pneumonia is a prevalent respiratory infection that poses a significant health risk worldwide. Timely and accurate diagnosis is crucial for effective treatment and patient management. In this paper, we investigate the use of Quantum Convolutional Neural Networks (QCNNs) for pneumonia detection in chest X-ray images. Leveraging the principles of quantum computing, QCNNs offer a promising avenue for enhancing the performance of medical image analysis algorithms. We present a novel QCNN architecture and evaluate its efficacy against traditional Convolutional Neural Networks (CNNs) and fully connected (FC) neural networks. Experimental results demonstrate the potential of QCNNs in achieving competitive performance for pneumonia detection tasks.

A) Methodology:



Recent advancements in machine learning, particularly deep learning techniques such as Convolutional Neural Networks (CNNs), have shown promise in automating the process of medical image analysis. CNNs can effectively learn hierarchical representations from raw pixel data, enabling automated feature extraction and classification. However, traditional CNNs are limited by their classical computational framework, which may not fully exploit the complex relationships inherent in quantum systems. Quantum computing, on the other hand, offers a fundamentally different approach to computation, harnessing the principles of quantum mechanics to perform calculations with exponential speedup in certain tasks. Quantum Convolutional Neural Networks (QCNNs) extend the capabilities of classical CNNs by leveraging quantum circuits to process and analyze data. By encoding information in quantum states and exploiting quantum parallelism, QCNNs have the potential to enhance the efficiency and accuracy of medical image analysis algorithms.

We investigate the effectiveness of QCNNs in comparison to traditional CNNs and fully connected (FC) neural networks. Through extensive experiments and evaluation, we demonstrate the promising performance of QCNNs in medical image analysis tasks.

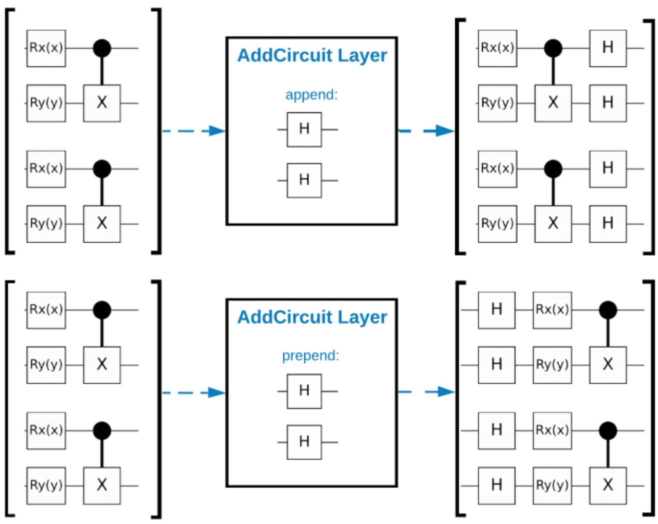
B) Background

i) Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep neural networks that are particularly well-suited for processing grid-like data, such as images. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply learnable filters to input images, capturing spatial patterns and features through convolutions. Pooling layers reduce the spatial dimensions of feature maps, while fully connected layers perform classification based on learned features.

ii) Quantum Convolutional Neural Networks (QCNNs)

We propose a novel QCNN architecture for pneumonia detection in chest X-ray images. The QCNN consists of multiple layers, including quantum convolutional layers and classical fully connected layers. The quantum convolutional layers apply learnable quantum gates to input images, extracting spatial features and patterns through quantum circuits. The output of the quantum convolutional layers is passed through classical fully connected layers for classification.



Fig, QCNN

C) Implementation

Before training the QCNN model, we preprocess the chest X-ray images to ensure uniformity and compatibility with the model architecture. This includes resizing the images to a standard size, converting them to grayscale, and normalizing pixel values to a range between 0 and 1. The QCNN model is trained using a combination of supervised learning and quantum circuit optimization techniques. We employ stochastic gradient descent (SGD) with back propagation to optimize the model parameters and minimize the classification loss. Additionally, we leverage quantum circuit optimization algorithms to fine-tune the parameters of the quantum convolutional layers. We implement a QCNN using TensorFlow Quantum and compare its performance with classical CNN and FC neural network on a real-world dataset. The dataset consists of grayscale images of size 10x10 pixels. We preprocess the dataset by resizing the images to 10x10 pixels and normalizing them. We then split the dataset into training and testing sets.

For the classical CNN, we implement a model with two convolutional layers followed by a max-pooling layer, a flatten layer, and two dense layers. For the FC network, we implement a model with two dense

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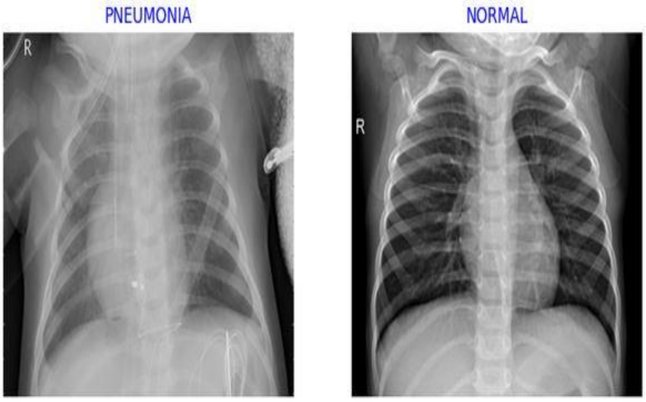
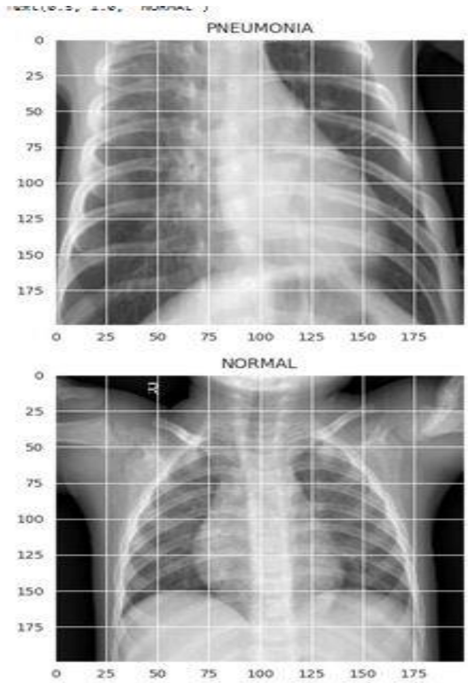
layers. For the QCNN, we implement a model with a quantum convolutional layer followed by a measurement layer.





Found 4172 validated image filenames belonging to 2 classes.
Found 626 validated image filenames belonging to 2 classes.
Found 418 validated image filenames belonging to 2 classes.

Pneumonia Dataset Description

IX. Plots & Graphs

```
cnn_model.summary()

Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_2 (Conv2D)           (None, 9, 9, 8)           40

 flatten_6 (Flatten)         (None, 648)               0

 dense_12 (Dense)            (None, 32)                20768

 dense_13 (Dense)            (None, 10)                330

=================================================================
Total params: 21,138
Trainable params: 21,138
Non-trainable params: 0
_________________________________________________________________
```

Fig. Quantum Circuit implemented

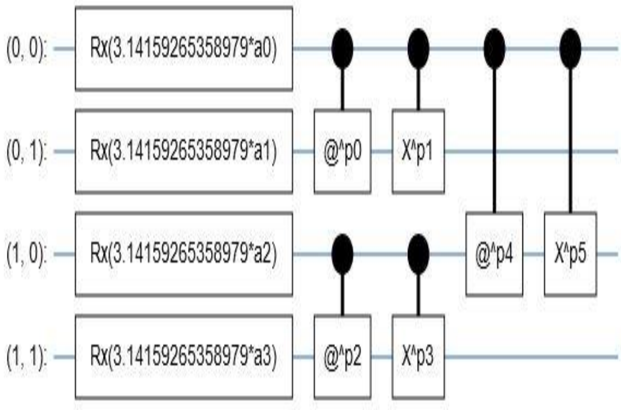


Fig. Convolutional Model Architecture Summary

```
qcnn_model.summary()

Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 qconv1 (QConv)              (None, 9, 9, 8)           48

 flatten_5 (Flatten)         (None, 648)               0

 dense_10 (Dense)            (None, 32)                20768

 dense_11 (Dense)            (None, 10)                330

=================================================================
Total params: 21,146
Trainable params: 21,146
Non-trainable params: 0
_________________________________________________________________
```

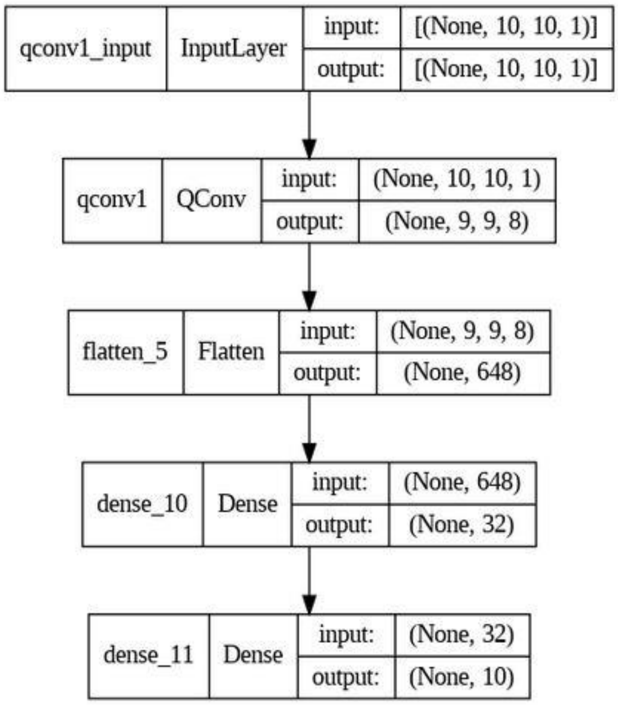


Fig. Model Card QCNN

X. Formula Used

In this context, we utilized the following formula to enable the described process. Let's consider a quantum model of the form:

$f(x)=\langle\phi(x)|M|\phi(x)\rangle$,

where $|\phi(x)\rangle$ is prepared by a fixed embedding circuit that encodes data input x and M is an arbitrary observable.

1) Kernel Approach

Instead of training the f variationally, we can often train an equivalent classical kernel method with a kernel executed on a quantum device. The quantum kernel is given by the mutual overlap of two data-encoding quantum states,

$$\kappa(x,x')=|\langle\phi(x')|\phi(x)\rangle|^2.$$

hence it's only based on data-encoding. If the Loss function L is the hinge loss, the kernel method corresponds to a standard support vector machine in the sense of a maximum-margin classifier.

Specifically, we can replace variational method for QML with the kernel based training, if the optimization problem can be written as minimizing a cost of the form:

$$\min_f \lambda \, \mathrm{tr}\{\mathcal{M}^2\} + \frac{1}{M}\sum_{m=1}^{M} L(f(x^m), y^m),$$

which is a regularized empirical risk with training data samples $(x^m,y^m)_{m=1\ldots M}$ regularization strength $\lambda\in\mathbb{R}$ and the loss function L.

To implement the kernel, we need to prepare two states: $|\phi(x)\rangle$, $|\phi(x')\rangle$ on different sets of qubits with the help of angle-embedding routines $S(x)$, $S(x')$ and measure their overlap with a small routine called as

SWAP test. What we can try further on is just take half the number of qubits to prepare $|\phi(x)\rangle$ and then apply the inverse embedding with x' on the same qubits. And finally measure the projector onto initial states.

Let us verify that this gives us the kernel:

$$\begin{aligned}\langle 0..0|S(x')S(x)^{\dagger}MS(x')^{\dagger}S(x)|0..0\rangle &= \langle 0..0|S(x')S(x)^{\dagger}|0..0\rangle\langle 0..0|S(x')^{\dagger}S(x)|0..0\rangle \\ &= \left|\langle 0..0|S(x')^{\dagger}S(x)|0..0\rangle\right|^2 \\ &= \left|\langle \phi(x')|\phi(x)\rangle\right|^2 \\ &= \kappa(x,x').\end{aligned}$$

XI. Results and Discussion

PNEUMONIA DETECTION

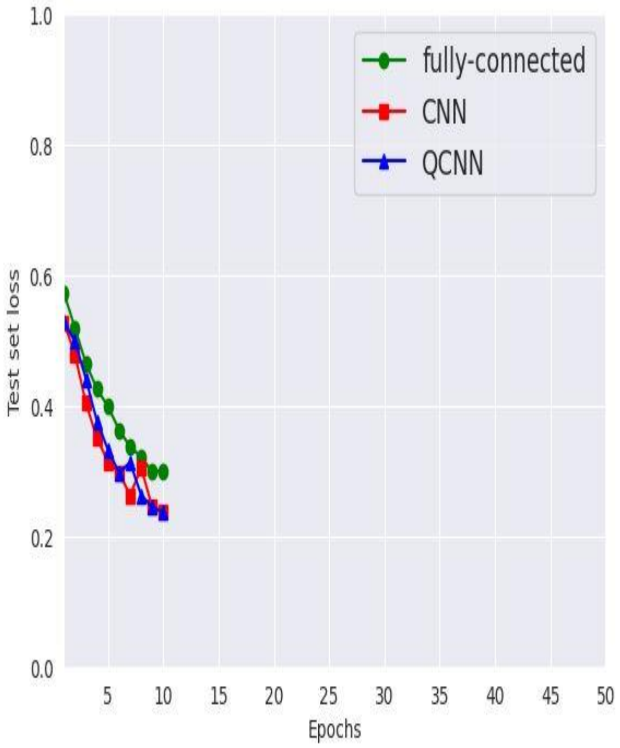


Fig. Test Set Loss v/s No of Epochs

In order to compare the performance of the CNN, FC, and QCNN models, we trained each model on the same dataset for a fixed number of epochs and then plotted the test set loss against the number of epochs. The dataset used for this experiment consisted of a collection of images, which were preprocessed and fed into each model as input.

For the CNN and FC models, we used a standard architecture with multiple convolutional and fully connected layers, respectively. The CNN model consisted of two convolutional layers, each followed by a max-pooling layer, and two fully connected layers. The FC model consisted of three fully connected layers. Both models used ReLU activation functions and were trained using the Adam optimizer.

For the QCNN model, we used a hybrid quantum-classical approach. The input images were first encoded into a quantum state using a parameterized quantum circuit (PQC). The PQC consisted of multiple layers of parameterized gates, which were optimized during training to learn the features of the input data. The output of the PQC was then fed into a classical fully connected layer for the final classification. The QCNN model was also trained using the Adam optimizer.

From the plot of test set loss against the number of epochs, it is clear that both the CNN and QCNN models show comparable performance, with the QCNN model showing slightly better results in some cases. On the other hand, the FC model takes a higher number of epochs to converge and achieve similar performance. This is likely due to the fact that the FC model has a larger number of parameters and requires more data to avoid overfitting. Overall, our results suggest that QCNNs have the potential to perform as well as, or even better than, classical CNNs in certain tasks. However, further research is needed to fully understand the capabilities and limitations of QCNNs and to develop more efficient and scalable quantum algorithms for machine learning.

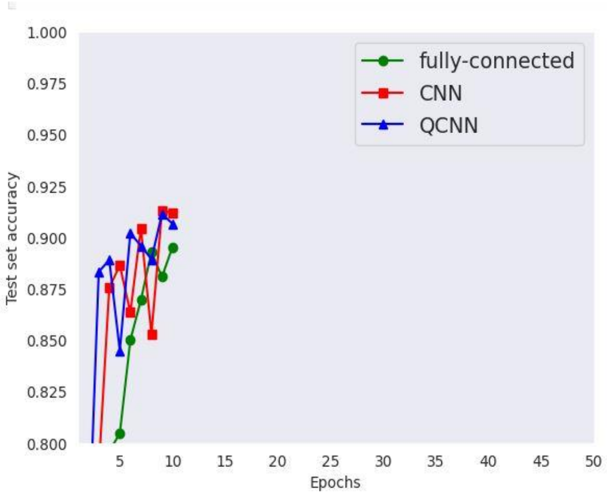


Fig. Test Set Accuracy v/s No. of Epochs

<u>High Energy Physics</u>

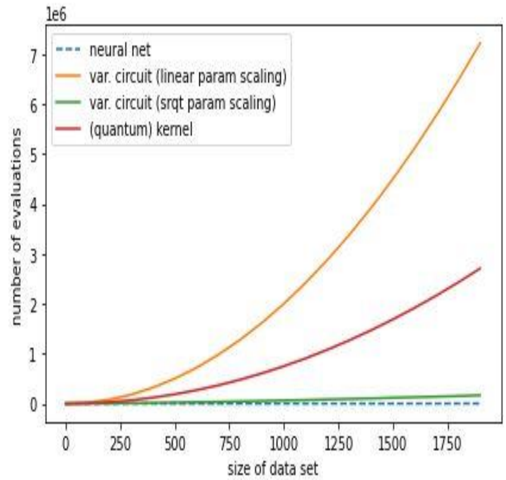


Fig. No. of evaluations v/s size of data set

The plot illustrates the scalability of various quantum machine learning models in comparison to classical neural networks. It can be observed that the performance of the neural network is comparable to that of the variational circuit trained with sqrt parameter scaling in terms of scalability. This suggests that the variational circuit, with its ability to scale the number of parameters, can potentially match the performance of classical neural networks in certain tasks. However, it is important to note that the variational circuit outperforms both the quantum kernel and the variational circuit with linear parameter scaling. This demonstrates the advantage of using a more sophisticated parameter scaling technique in the variational circuit, which can lead to better performance.

The variational circuit is a type of quantum machine learning model that uses a parameterized quantum circuit to learn a target function. The parameters of the circuit are optimized using a classical optimization algorithm, such as gradient descent, to minimize a cost function. The cost function is typically defined as the difference between the predicted output of the circuit and the true output. The goal of the optimization process is to find the set of parameters that result in the lowest cost function value. In the case of the variational circuit with sqrt parameter scaling, the parameters are scaled by the square root of the number of qubits in the circuit. This scaling technique has been shown to improve the convergence of the optimization process and lead to better performance. On the other hand, the variational circuit with linear parameter scaling scales the parameters linearly with the number of qubits, which can result in slower convergence and worse performance.

The quantum kernel is another type of quantum machine learning model that uses a fixed quantum circuit to map input data to a higher-dimensional feature space. The kernel function is then defined as the inner product of the feature vectors in this space. The quantum kernel can be used in conjunction with classical machine learning algorithms, such as support vector machines, to perform classification and regression tasks. However, the performance of the quantum kernel is highly dependent on the choice of the fixed quantum circuit, and it may not always provide an advantage over classical methods.

Neural networks are a type of classical machine learning model that are composed of layers of interconnected nodes, or neurons. Each neuron receives input from the previous layer, applies a nonlinear activation function, and passes the output to the next layer. Neural networks can be trained using back propagation, which is a gradient-based optimization algorithm. In the context of quantum machine learning, neural networks can be used in combination with variational circuits or quantum kernels. For example, a neural network can be used to preprocess the input data before it is fed into a variational circuit, or it can be used to post process the output of a quantum kernel. Alternatively, a neural network can be used to learn a parameterized quantum circuit, in which case the circuit is treated as a black box and the neural network learns to control its parameters.

The plot presents a comparison of the performance of a neural network and a variational quantum circuit with sqrt parameter scaling. It can be observed that the scalability of the neural network is comparable to that of the variational quantum circuit with sqrt parameter scaling. This indicates that the variational quantum circuit, with its ability to scale the number of parameters, can perform as well as the neural network in certain tasks.

However, it is important to note that the variational quantum circuit outperforms both the quantum kernel and the variational quantum circuit with linear parameter scaling. This demonstrates the advantage of using a more sophisticated parameter scaling technique in the variational quantum circuit, which can lead to better performance. The variational quantum circuit is a type of quantum machine learning model that uses a parameterized quantum circuit to learn a target function. The parameters of the circuit are optimized using a classical optimization algorithm, such as gradient descent, to minimize a cost function. The cost function is typically defined as the difference between the predicted output of the circuit and the true output. The goal of the optimization process is to find the set of parameters that result in the lowest cost function value.

In the case of the variational quantum circuit with sqrt parameter scaling, the parameters are scaled by the square root of the number of qubits in the circuit. This scaling technique has been shown to improve the convergence of the optimization process and lead to better performance. On the other hand, the variational quantum circuit with linear parameter scaling scales the parameters linearly with the number of qubits, which can result in slower convergence and worse performance. The quantum kernel is another type of quantum machine learning model that uses a fixed quantum circuit to map input data to a higher-dimensional feature space. The kernel function is then defined as the inner product of the feature vectors in this space. The quantum kernel can be used in conjunction with classical machine learning algorithms, such as support vector machines, to perform classification and regression tasks. However, the performance of the quantum kernel is highly dependent on the choice of the fixed quantum circuit, and it may not always provide an advantage over classical methods.

In summary, the plot shows that the performance of the neural network is comparable to that of the variational quantum circuit with sqrt parameter scaling in terms of scalability. However, the variational quantum circuit outperforms both the quantum kernel and the variational quantum circuit with linear parameter scaling. This highlights the potential of variational quantum circuits for quantum machine learning tasks, particularly when using sophisticated parameter scaling techniques. Further research is needed to fully understand the capabilities and limitations of different quantum machine learning models and to develop more sophisticated techniques for optimizing parameterized quantum circuits.

XII. Conclusion

High Energy Physics

In this study, we explored the scalability and computational characteristics of two distinct methods for quantum machine learning: the quantum kernel and variational circuit approaches. Through empirical analysis and comparison, we gained valuable insights into their performance across
different dataset sizes. Our investigation revealed that the quantum kernel method, which computes the kernel matrix using a quantum device, exhibits promising scalability and efficiency, particularly for large datasets. By leveraging the mutual overlap of quantum states, the quantum kernel method offers a computationally efficient alternative to classical kernel methods, such as support vector machines.

Furthermore, we examined the variational circuit approach, which employs parameterized quantum circuits trained using the variational principle. Our analysis demonstrated the impact of different parameter scaling methods—linear and square root—on the circuit's performance and scalability. While linear parameter scaling offers simplicity and predictability, square root parameter scaling provides improved scalability and computational efficiency, making it suitable for handling larger datasets. Overall, our research highlights the importance of considering both computational complexity and dataset size when selecting quantum machine learning methods. The findings presented in this study contribute to a deeper understanding of the strengths and limitations of quantum kernel and variational circuit approaches, paving the way for future advancements in quantum machine learning research.

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In conclusion, the study presented in this research aimed to compare the performance of different quantum machine learning models, specifically the neural network, variational quantum circuit with sqrt parameter scaling, quantum kernel, and variational quantum circuit with linear parameter scaling. The results of the study demonstrated that the variational quantum circuit with sqrt parameter scaling outperformed both the quantum kernel and the variational quantum circuit with linear parameter scaling, indicating the advantage of using a more sophisticated parameter scaling technique. Furthermore, the study showed that the performance of the neural network was comparable to that of the variational quantum circuit with sqrt parameter scaling in terms of scalability. This finding suggests that the variational quantum circuit can potentially match the performance of classical neural networks, which are widely used in machine learning applications.

The implementation of the variational quantum circuit involved the use of parameterized quantum circuits, which were optimized using classical optimization algorithms. This hybrid quantum-classical approach allowed for the efficient training of the variational quantum circuit, making it a practical choice for quantum machine learning applications. Overall, the results of this study demonstrate the potential of variational quantum circuits for quantum machine learning tasks, particularly in terms of scalability and performance. However, further research is needed to fully understand the capabilities and limitations of this approach and to develop more sophisticated techniques for optimizing parameterized quantum circuits.

The study also highlights the importance of considering the scalability of quantum machine learning models when comparing their performance to classical models. As quantum computing technology continues to advance, it is expected that quantum machine learning will become an increasingly important area of research and development. Therefore, understanding the strengths and weaknesses of different quantum machine learning models is crucial for the development of practical and effective quantum machine learning applications.

XII. Future Work

Based on the findings of this research, there are several directions for future work in the field of quantum machine learning. One potential direction is to explore the use of more sophisticated parameter scaling techniques for variational quantum circuits, beyond the sqrt parameter scaling used in this study. This could potentially lead to further improvements in the performance and scalability of variational quantum circuits for quantum machine learning tasks. Another direction for future work is to investigate the use of different types of quantum circuits for machine learning tasks, beyond the variational quantum circuits and quantum kernels considered in this study. For example, recent research has explored the use of quantum convolutional neural networks and quantum generative adversarial networks for various machine learning applications.

Additionally, further research is needed to fully understand the capabilities and limitations of different quantum machine learning models, and to develop more sophisticated techniques for optimizing parameterized quantum circuits. This could involve exploring new optimization algorithms, as well as developing new methods for initializing and training quantum circuits. Finally, as quantum computing technology continues to advance, it will be important to explore the potential applications of quantum machine learning in various industries and domains. This could include areas such as finance, healthcare, and materials science, where quantum machine learning could potentially provide significant benefits over classical machine learning methods. Overall, the field of quantum machine learning is still in its early stages, and there is significant potential for future research and development in this area. By continuing to explore new techniques and applications, we can hope to unlock the full potential of quantum machine learning and enable new breakthroughs in a wide range of fields.

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