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Research Oriented Reviewing of Quantum Machine Learning

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Abstract

Quantum machine learning is an interdisciplinary research domain that seeks to merge the concepts of quantum computing and machine learning. Owing to the computational complexity and time constraints of certain scientific challenges, classical computation is often inadequate, and quantum computation offers a promising alternative. Notable algorithms in quantum machine learning include quantum versions of classical machine learning algorithms, such as support vector machines, and classical deep learning techniques, such as quantum neural networks. The primary aim of quantum machine learning is to improve the performance of machine learning by leveraging quantum computing. While there have been promising advances, quantum machine learning still requires significant advancements in quantum hardware to fully realize its potential.

1. Introduction

Machine learning is a subfield of computer science that deals with the discovery of patterns from data to make sense of previously unintelligible inputs. It is a technique that utilizes algorithms to process large amounts of data for tasks that the human brain is inherently good at, such as pattern recognition, speech recognition, image recognition, and strategy optimization. The foundation of current data mining and data visualization techniques lies in algorithms for optimizing constrained multivariate functions, which is the fundamental concept of machine learning. The decision function maps input and output points, and optimization is the result of this process. While there are exceptions to this oversimplified rule, such optimizations are essential to learning theory and are used in the creation of artificial intelligence. Three techniques that have historically been employed in machine learning are supervised machine learning, unsupervised machine learning, and reinforcement learning (Schuld). In supervised machine learning, computers are trained to operate using data that has already been labelled with some features, while in unsupervised machine learning, machines examine data without labels, identifying patterns based on similarities and differences between classes (Mishra et al.). Reinforcement learning, on the other hand, enables machines to learn by analyzing feedback.

The annual amount of data saved globally has increased by 20%, thereby expanding the need for novel machine learning techniques . The application of quantum computing to optimize conventional machine learning techniques has become a primary focus for academic institutions and top IT businesses. The convergence of modern physics and engineering has facilitated the development of advanced techniques, such as Grover's Search, Shor's Factoring, and Linear Systems Algorithms, which have the potential to transform existing paradigms. Quantum Machine Learning, the amalgamation of quantum computing and deep learning, presents a promising new field with extraordinary potential .

Quantum phenomena such as superposition and entanglement, when applied to classical machine learning gives birth to concept of Quantum Machine Learning. The basic data processing components used in quantum systems are called qubits (quantum bits). Like binary values, which can only be either 0 or 1, a qubit is not constrained to a two-state solution but can also reside in superposition. As a result, qubits can be used concurrently at 1 and 0 as well as 0 and 1. It can perform many calculations in parallel because it can chase simultaneous probabilities through superposition and manipulate them with magnetic fields. Furthermore, because of this, quantum computers are capable of supersonic computation of extremely complex tasks. Qubits also have the intriguing feature that, even if we do not yet know what the results are, their superpositions can be logically linked to those of other qubits by pairing. Because of this, changing the state of one qubit will immediately and predictably change the other. Businesses may therefore have instant contact relays . We develop quantum algorithms to execute the conventional algorithms used in quantum machine learning techniques using a quantum computer. Data can be categorized, sorted, and analysed by using quantum algorithms for supervised and unsupervised learning methods. Once more, these methods are applied using models of a support vector machine or a quantum neural network.

The development of quantum versions of artificial neural networks, which are frequently used in machine learning, has attracted some attention, but because they frequently adopt a more biological approach, no major progress has yet been made . Some authors make an effort to develop complete quantum algorithms that deal with pattern identification problems. Other approaches merely suggest running classical machine learning algorithm subroutines on a quantum computer to boost performance (Sharma). An intriguing approach that seems particularly suitable for some subsets of optimization problems is adiabatic quantum machine learning. It is skilfully done to transform stochastic models like hidden Markov models and Bayesian decision theory into the language of open quantum systems (Chowdhury). The comprehensive theory of quantum learning, or how quantum information might potentially be used in intelligent computing, is still in its infancy despite the growing interest in the topic. Before discussing quantum computing and subsequently quantum machine learning, it is important that we are acquainted with the terms listed below.

1.1. The Bloch Sphere

The Bloch Sphere is a geometrical illustration of a qubit. The state of a qubit is represented by a two-dimensional vector with a usual length of one. This vector is composed of two numbers: a real number and a complex number.

1.2. Quantum Decoherence

Quantum Decoherence-related issues are brought on by qubit combination. Unwanted collapses like these happen erratically and naturally as a consequence of system disturbance. In the end, this leads to computation mistakes. The outcome won't be what you might have expected when we operate on a qubit that you think is in a state but isn't.

1.3. Quantum Entanglement

According to the theory of quantum entanglement, two qubits are always superposed in two distinct states. The other is automatically placed in a spin-down position if one is rotating up. It is impossible for both qubits to be in the same state at the same time. To put it another way, they are constantly entangled. What's taking place in this case is quantum coupling.

1.4. Dual Principle

Qubits resemble both waves and particles in their characteristics. In actuality, everything does, but the qubit's atomic size makes them simpler to observe. Qubits can interact with one another through interference because of the wave-particle duality.

1.5. Quantum Speedup

Due to quantum coherence, the quantum computer can process information in a manner that is not possible for classical computers. A quantum algorithm approaches problems, like database queries, in a step-by-step manner. It can outperform the most widely used traditional algorithms. This phenomenon is known as the Quantum Speedup.

This paper provides an overview of the rapidly developing subject of quantum machine learning, outlining its significance, uses, benefits, and disadvantages. Discussions about quantum computing and its necessity will also be present. Three case studies will be discussed in the final sections of the paper to help readers better grasp QML's advantages.

2. Benefits of QML

One of the main benefits of quantum computers is the possible increase in computation speed. Depending on the issue and algorithm, respectively, quantum algorithms can be exponentially or polynomially faster than classical algorithms. Quantum computers might be better able to handle noisy data, learn from fewer inputs, or comprehend more complex structures. The three primary advantages of quantum machine learning are, in brief:

2.1. Improvements in run-time: obtaining faster results; Quantum Hybrid Helmholtz Machine

Hybrid algorithms, which combine classical and quantum computing, profit from particular advantages like effective sampling. These hybrid techniques offer a solution to issues with traditional processing in generative modeling. These generative models can be used to train probability distributions over (high dimensional) data sets, for instance.

A generative model's depth can be increased to find more abstract models of the data, but doing so incurs intractably high inference and training costs. Both inference and training are carried out using computationally costly methods such as Markov Chain Monte Carlo sampling and variational approximations. Since quantum computers are capable of effective sampling, the costly sampling subroutine can be executed on them, significantly reducing the computational complexity of generative models. This can be used to build a composite Helm-Holtz machine, a specific type of generative model, on a gate-based quantum computer or an annealing device.

A top-down generative network and a bottom-up detection network combine to form a Helmholtz machine, a particular kind of artificial neural network. The recognition network accepts data and constructs probability distributions over it, whereas the generative network generates representations of the input and hidden variables.

2.2. Learning capacity improvements: increase of the capacity of associative or content-addressable memories; Quantum Hopfield Neural Network

A type of machine learning algorithms known as neural networks consists of nodes that can be connected in various ways and communicate with one another via weighted edges. One exception is Hopfield neural networks (HNN), which do not self-connect and have a single layer of nodes connected to one another by symmetric edges. HNNs can be used as associative memories because they can remember a variety of patterns and link noisy inputs to the nearest stored pattern. With the help of training techniques like Hebbian learning, the network can be trained to recall memory patterns. In this instance, all memory patterns are used to directly compute the weights, requiring little computational work.

An HNN may contain an exponentially large number of stable attractors if the collection of attractors is predetermined and fixed. HNNs' storage capabilities are, however, usually limited if patterns are selected at random because there is typically less that can be saved.

For Hebbian learning, an HNN with n nodes has a storing capacity of n/(4 log n) patterns asymptotically. It is believed that converting HNNs into their quantum equivalents will increase storage capacities beyond what is currently feasible with traditional networks. For instance, it is proposed a quantum HNN that, when qutrits are used, might provide an exponential capability.

2.3. Learning efficiency improvements: less training information or simpler models needed to produce the same results or more complex relations can be learned from the same data; Variational Quantum Circuit for Machine Learning

An especially well-liked technique for developing innovative hybrid QML algorithms is the use of variational quantum circuits (VQC), which are composed of several optimized quantum gates. These quantum devices allow for the evaluation of a cost function. To optimize the cost function, which may once more entail a quantum circuit, a variety of classical techniques can be used.

3. Need for Quantum Computing

One of the major impetuses for the development of quantum computers is the approaching plateau of classical computers. Moore's law predicts that the rate of transistor growth on computer chips will shortly plateau. There is no economic reason for this; it is simply an outcome of physics principles. Transistors of the latest generation have a size of about 10 nanometers. It has been established that transistors begin to feel the effects of quantum tunneling at a distance of less than seven nanometers. When the thickness of a gate hits a certain value, an electron can "jump" over the barrier, allowing current to flow in an unintended direction. When barriers in the transistor grow arbitrarily tiny, this phenomenon results. Due to this non-classical effect, the transistors are essentially useless. Even though it's possible that chip manufacturers will be able to partially avoid this effect, the size of the transistor will basically reach its maximum very soon.

Quantum bits, also referred to as qubits, are used in quantum computers instead of tiny transistors because they take advantage of the same quantum phenomena that cause chaos in conventional systems. Due to superposition, each extra qubit is equivalent to doubling the computer's power. This stands in stark contrast to the fact that twice as many transistors would be needed to give a typical computer twice the processing capacity.

It is expected that using quantum computing will have advantages over using traditional hardware. For instance, Shor's factoring algorithm is one of these early benefits. This algorithm will accelerate the factoring procedure almost exponentially. This method is put forth as a means of breaking the RSA (Rivest-Shamir-Adleman) security system. Grover's algorithm also employs phase amplification to find items in an unsorted database. This could, among other things, be used in graph theory or machine learning. And finally, the quantum linear systems approach is especially well suited to machine learning.

4. Applications

In this section, we will discuss some methods that quantum computers use to solve machine learning problems.

4.1. QML to solve linear algebraic problems

Many different Data Analysis and Machine Learning problems are handled by using matrix operations on vectors in a high dimensional vector space. In a 2a-dimensional complex vector space, the quantum state of a qubit in a quantum computer is a vector. Numerous matrix transformations occur in this region. Quantum computers effortlessly handle the Fourier Transform, finding eigenvectors and eigenvalues, and solving linear sets of equations over 2a-dimensional vector spaces in polynomial time. (and exponentially faster than classical computers due to the Quantum Speedup). One example is the Harrow, Hassidim, and Lloyd (HHL) method.

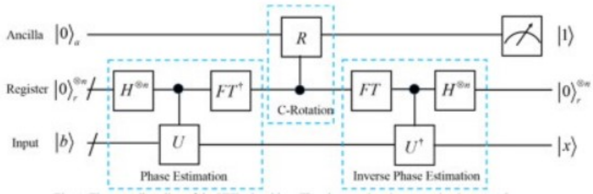

FIGURE 1. Circuit Diagram of the HHL Algorithm

Quantum Principal Component Analysis

Principal component analysis is a dimensionality reduction technique that can be used to decrease the number of dimensions in large datasets. Since we must choose which variables to remove without losing important data, accuracy must be sacrificed in order to decrease the dimensions. Dealing with a smaller dataset is significantly more practical when done properly, which greatly simplifies the machine learning work.

A dataset with ten input attributes, for instance, can be effectively analyzed using principal component analysis using a conventional computer. However, if the input dataset contains a million features, the conventional techniques of principal component analysis will not be effective because it will be challenging to demonstrate the relative importance of each feature.

Another issue with conventional processors is the computation of eigenvectors and eigenvalues. The more dimensional the input, the larger the collection of related eigenvectors and eigenvalues becomes. Quantum computers can handle this issue swiftly and effectively thanks to quantum random access memory (QRAM), which chooses a data vector at random. The vector is converted into a quantum state using qubits. The summed vector that emerges from quantum principal component analysis contains logarithmic qubits. The resulting random vector is a compact matrix. the matrix of correlation.

Using the quantum phase estimation algorithm, density matrix exponentiation, and repeated data sampling, we can take the quantum version of any data vector and decompose it into its main components. (which determines the eigenvectors and eigenvalues of the matrices). As a result, both the complexity of calculation and the complexity of time are decreasing exponentially.

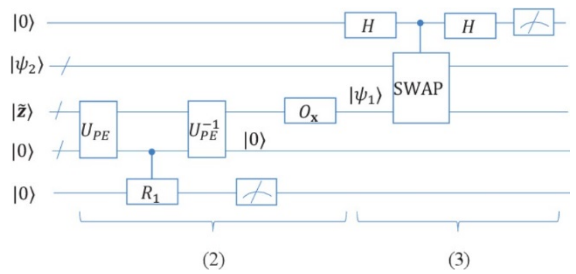

FIGURE 2. Quantum Circuit to perform Principal Component Analysis

4.2. Quantum Support Vector Machines

Both categorization and regression are performed using the Support-Vector-Machine, a well-known machine learning technique. It is used to divide datasets that can be linearly separated into the proper groups for classification tasks. Let's assume the dimensions of the data are expanded until they can be separated linearly if they can't already. SVM is limited to a certain number of dimensions on classical machines. After a certain point, it will become challenging because such computers lack sufficient computing capacity.

On quantum computers, however, the Support Vector Algorithm can be run exponentially more rapidly. The superposition and entanglement principles allow for more efficient operation and faster outcomes.

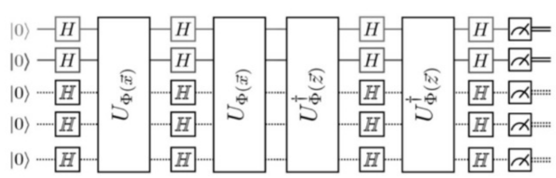

FIGURE 3. Quantum Circuit to perform SVM

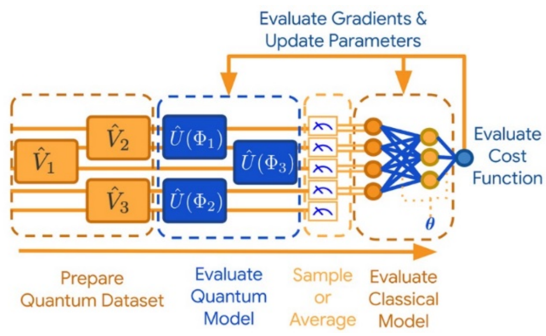

FIGURE 4. Deep Quantum Learning

4.3. Quantum Optimization

A machine learning algorithm makes use of optimization to speed up the learning process and generate the most complete and precise estimates. The main objective of optimization is the reduction of the loss function. More inaccurate and unreliable outputs will be produced as a result of an increased loss function, which can be costly and produce erroneous predictions.

Most machine learning methods call for iterative performance optimization. Quantum methods for optimization suggest that machine learning optimization issues will get better. The quantum entanglement property enables multiple copies of the present answer, encoded in a quantum state. They are utilized at each step of the machine learning algorithm to improve that response.

4.4. Deep Quantum Learning

The formation of neural networks can be accelerated by combining deep learning and quantum computing. By employing this method, we could achieve deep optimization and develop a fresh deep learning system. We demonstrate that conventional deep learning techniques can be replicated on a real, physical quantum computer. When using multilayer perceptron topologies, the computational difficulty increases with the number of neurons. Using specialized GPU groups can improve performance while drastically reducing training time. However, even this will be outpaced by quantum processors.

Rather than using the software found in conventional computers, the technology in quantum computers is designed to mimic neural networks. In this case, a qubit plays the part of a neuron, the basic unit of a neural network. As a result, a quantum system with qubits can be used for deep learning applications at a rate that is faster than any conventional machine learning method to accomplish the task of a neural network.

5. Disadvantages

Quantum computing is the answer to many problems, but it is not without its limitations and challenges due to its reliance on fundamental physics and the primitive state of other technologies that aid in the hardware and software development of quantum computers, on which complex algorithms can be built and run.

5.1. Hardware Limitations

One issue that frequently afflicts academics is isolation. Qubits may lose quantum properties like entanglement when exposed to heat or light, which further reduces the quantity of data they can hold. These two factors can also cause quantum decoherence. Second, even though they are crucial for changing the state of the qubit, spins in the logic gates of quantum computers are prone to error. Any incorrect rotation could cause a problem with the product. Additionally necessary for the area of quantum machine learning are computers with longer circuit lengths and error correction (with redundancy for every qubit).

5.2. Software Limitations

When creating programs for quantum computers, one must take into account their physics. The Turing machine can be used to build a classical algorithm, but a quantum algorithm must be developed in the style of pure physics without the aid of any simple formulas that would link it to logic.

In a system of this type, scalability is always of utmost importance. modifying a program to have more processing power in order to manage larger data. The amount of information required to develop these quantum computing algorithms is quite small. As a result, the growth is largely intuitive. It is challenging to develop models that have a significant impact on machine learning because the actual applicability of the majority of well-known quantum algorithms is constrained by the limitations of some simulations. The maximum amount of qubits that can be arranged on a quantum circle is the third limitation on quantum computing. Despite the fact that these limitations apply to all forms of quantum computing, the inclusion of fields like machine learning can boost interest and steer study in the right directions.

6. Security Intrusion Detection: Case Study I

Even the most sophisticated machine learning (ML)-based detectors suffer from poor quality and performance when dealing with big data inputs: model training and application using a traditional ML detector run on a big data input on a typical computing device may result in accurate outputs but take a very long time, or it may be trained and calculated quickly but perform with poor accuracy of outputs, both of which are at odds with malicious activity characteristics like intrusion variability, intensities, and so on. In this case study, as seen in (Tian and Baskiyar), we emphasise the innovative quantum machine learning approach used in intrusion detection, particularly when dealing with large inputs. As intrusion detection as a security relative task requires quick and accurate detectors, QSVM and QCNN computing models were mainly discussed in the referred paper for case study. The main aim of the case study is to investigate and compare the basic QML models and understand their superiority while processing big data.

Figures 5,6,7 and 8 display the outcomes of experiments that were done to solve the classification problem using the conventional SVM and its quantum implementation, QSVM, on a massive data input (> 106 records). Only HTTP Flooding and Port Scanning attacks are accurately recognised when using the traditional SVM.

A large majority of the remaining classes' accuracy falls between the ranges of 0.4 and 0.8. The ACK Flooding attack's network streams were essentially undefinable. The categorization was carried out with a 98% accuracy using QSVM.

The outcomes of the trials using the traditional CNN and its quantum implementation, QCNN, are displayed in Figures 9,10,11 and 12. The superiority of the quantum technique over the traditional one is also shown by neural networks. The confusion matrix indicates that, like with the QSVM, 98% of typical packets can be detected accurately. The ROC curves show that QCNN outperforms QSVM in terms of performance.

The training times for the various quantities of input datasets used by the QML algorithms are shown in Table 1 for comparison. On a large input, QSVM and QCNN can be trained around twice

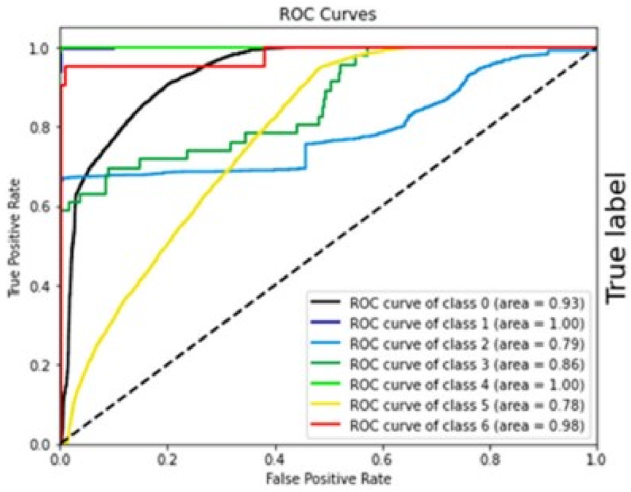

FIGURE 5. **Graph of Intrusion detection results with conventional SVM**

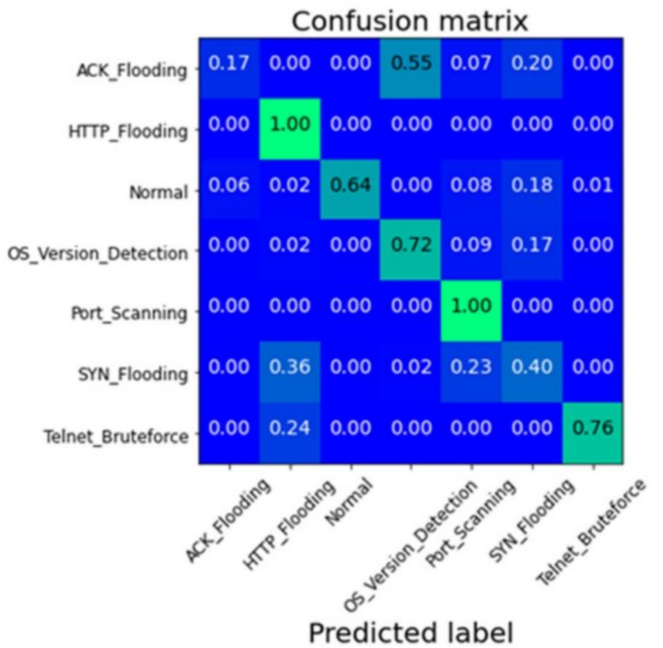

FIGURE 6. **Intrusion detectionresults with conventional SVM**

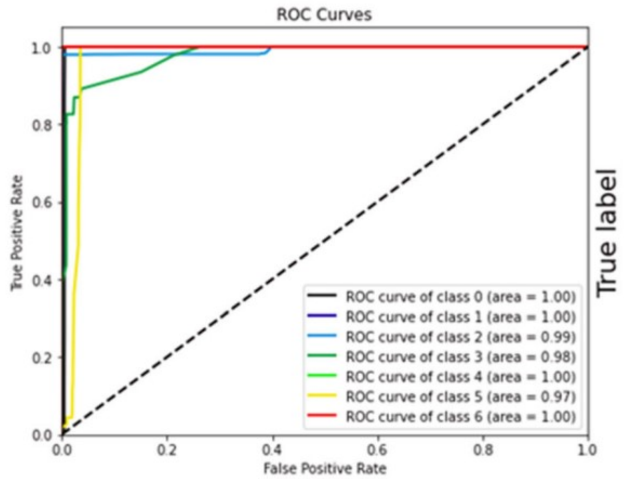

FIGURE 7. **Graph of Intrusion detection results with QSVM**

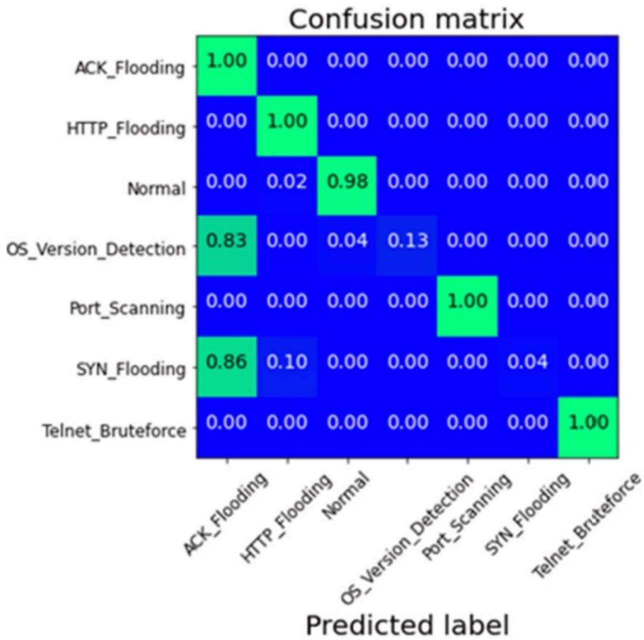

FIGURE 8. **Intrusion detection results with QSVM**

as quickly, and this priority increases as the input data volume increases. The QML on the Tensorflow Quantum framework is also used to achieve the QML classifier's priority on the same datasets. The trials' findings have shown that QML is superior to traditional ML-based detectors in classifying large amounts of input data.

The QML-based intrusion detection method is more effective than a conventional ML method when protecting a large-scale network with a large volume of security-relevant data. The promise of the quantum apparatus on big data inputs has been demonstrated by comparison of the QML detectors built on the QSVM and QCNN classifiers against the traditional SVM and QCNN detectors.

Both in accuracy and performance, the QML-based approaches have overtaken the ML-based implementations. The quantum technique clearly outperforms the traditional ML classifiers when compared to them on large stream datasets (e.g., QSVM and QCNN classification accuracy is 98%).

The training time has been cut in half or more as a result of QML.

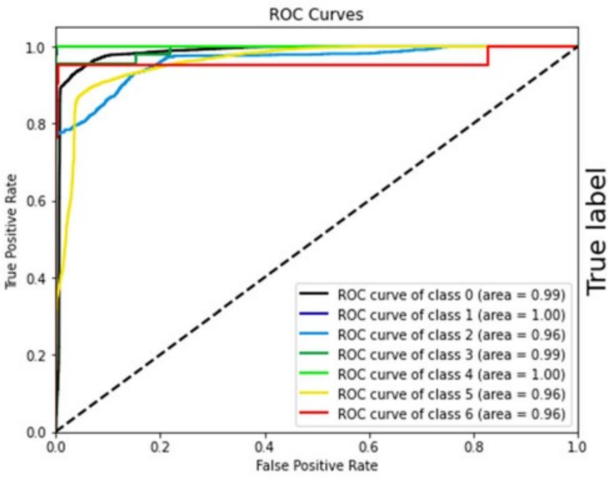

FIGURE 9. **Graph of Intrusion detection results with the conventional CNN**

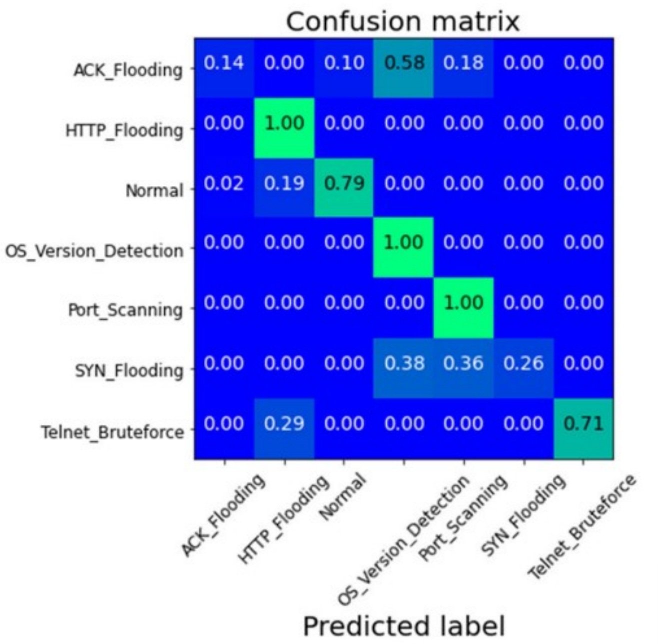

FIGURE 10. **Intrusion detection results with the conventional CNN**

We found that the QCNN detector is more promising when comparing the QSVM and QCNN detectors, despite the QSVM being faster. The method's complexity is decreased by the QCNN's capacity to choose the most important characteristics with a higher probability. The QCNN's flexibility in changing the size of the cores and the number of layers it uses to solve classification problems is another benefit.

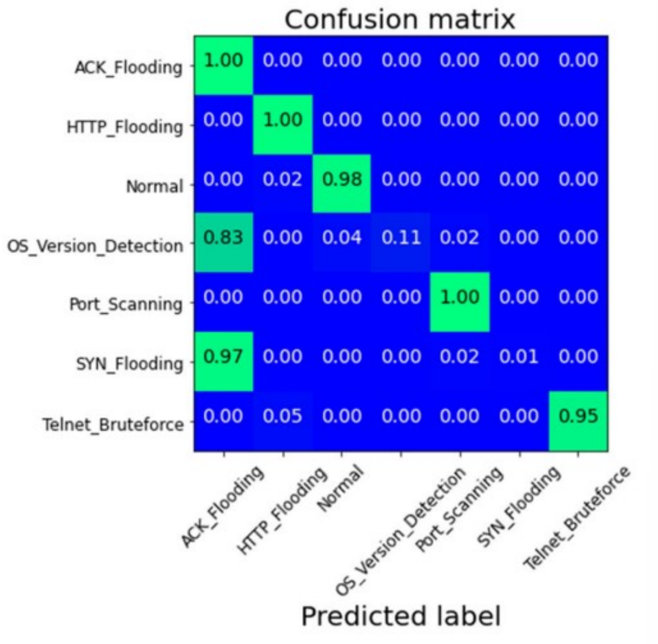

FIGURE 11. **Intrusion detection results with the QCNN**

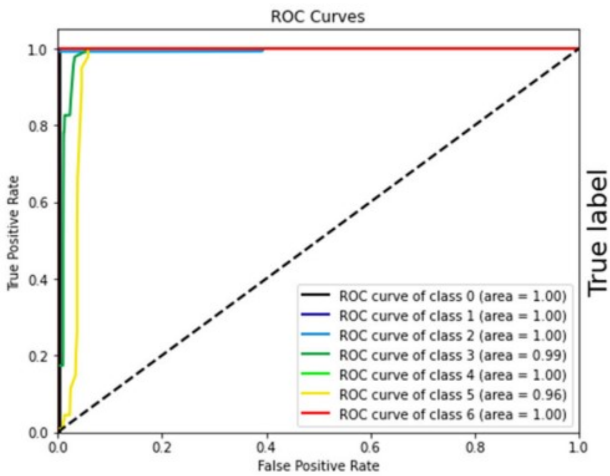

FIGURE 12. **Graph of Intrusion detection results with the QCNN**

Input size (samples)	SVM training (hrs)	QSVM training (hrs)	CNN training (hrs)	QCNN training (hrs)
100,000	0.5	0.4	0.7	0.5
200,000	1.4	0.8	1.8	0.9
300,000	2.2	1.3	2.5	1.4
400,000	3.1	1.7	3.3	1.9
500,000	4.4	2.3	4.9	2.7
600,000	5.9	3	6.9	3.6
700,000	6.8	3.3	7.7	3.9
800,000	7.7	3.8	8.5	4.8
900,000	8.9	4.5	9.3	4.9
1,000,000	9.6	5.2	10.9	5.6
2,500,000	12.6	6.1	15.5	6.8
5,000,000	16.9	8	26.9	9.9
10,000,000	22.4	10.6	36.7	14.5

FIGURE 13. **QML and conventional ML training time**

7. Covid-19 Classification: Case Study II

The case study provided in (Foy) investigates the QML and classical machine learning approaches for the analysis of covid-19 images. It consists of 2 phases: in phase I, synthetic CT images are generated, through the conditional adversarial network (CGAN) to increase the size of the dataset for accurate training and testing. In phase II, the classification of COVID-19/healthy images are performed, in which two models are proposed: CML and QML.

Synthetic data is generated by applying a modified Conditional Generative Adversarial Network architecture. These images are supplied to Classical Machine Learning and Quanvolutional Neural Network models.

7.1. CML Model

The CML model is proposed for classification which comprises three kinds of layers such as 01 convolutional, 01 fatten, and 02 dense layers. The convolutional layers are primary building blocks in CNN, which maps the input images size of 128 × 128 × 3 with 3 × 3 kernel size and output in the form of activation which is mathematically explained as follows:

G[m, n] = (f * h)[m n] = $\sum_j \sum_k$ h [j, k] f [m-j, n-k]

where f denotes input images, h represents kernel size, and m, n symbolizes the row and column, respectively. The fatten layer is applied to collapsed spatial input dimensions into channel dimension height × width × channel. The dense layer is the layer of a regular neuron of the neural network, in which neurons receive input from all neurons from the preceding layers and connected densely.

Output = activation(dot(input, kernel) + bias

The ReLU and softmax activation functions are utilized with the number of neurons such as 13 and 02, respectively. The model is trained on the hyperparameters that are selected after the comprehensive experiment as shown in figure 14.

7.2. QNN Model

A new QNN contains three kinds of layers, such as 4-Qubit-quantum layers, 03-dense layers with specified activation units, and drop-out layers. The quantum layer is added to replace the convolutional layer. The 4-bit quantum is used to generate the 20 × 20-dimension quantum images. The quantum generated images are learned in a pipeline; then, a dense layer by ReLU and softmax with different activation units are applied. The model learning parameters are the same as CML model for the fair comparison among these two architectures such as CML and QNN.

Optimizer	RMSprop
Batch-Size	26
Epochs	100
Loss	Sparse categorical cross-entropy

FIGURE 14. Training hyperparameters of the CML model

The quantum generated images are transferred to QNN, where 03 dense layers are used by 60, 500 neurons with ReLU activation and 02 neurons with softmax for features mapping. The 0.5 drop-outs are utilized.

These 2 models are evaluated using 2 datasets, the UCSD-AI4H/COVID-CT dataset and a dataset collected from POF Hospital Pakistan. Table 3 provides a comprehensive overview of the datasets

The result for both models are given in the form of tables and graphs.

Figure 16 presents the classification results using CML and QNN models using 0.4 and 0.5 cross-validation on the benchmark datasets, where the red line and blue line show the results of quantum (QNN model) and without quantum layers (CML-model) respectively.

Lung CT images are classified using two architectures such as CML and QNN.

Ref	Datasets	Method	Results (Fe)
Yang et al. [53]	UCSD-AI4H/ COVID-CT	50 residual model	0.89 AC
Horry et al. [54]		VGG-16	0.79
		VGG-19	0.78
		Xception	0.70
		Inception ResNet	0.63
		Inceptionv3	0.71
		NasNet large	0.64
		DenseNet121	0.75
		ResNet50v2	0.66
Burgos [55]		Inception	0.85
Wang et al. [56]		COVID-Net	0.78
Ewen and Khan [57]		DenseNet169	0.87
Proposed method		**QNN**	**0.96**

FIGURE 15. Comparison of the outcomes

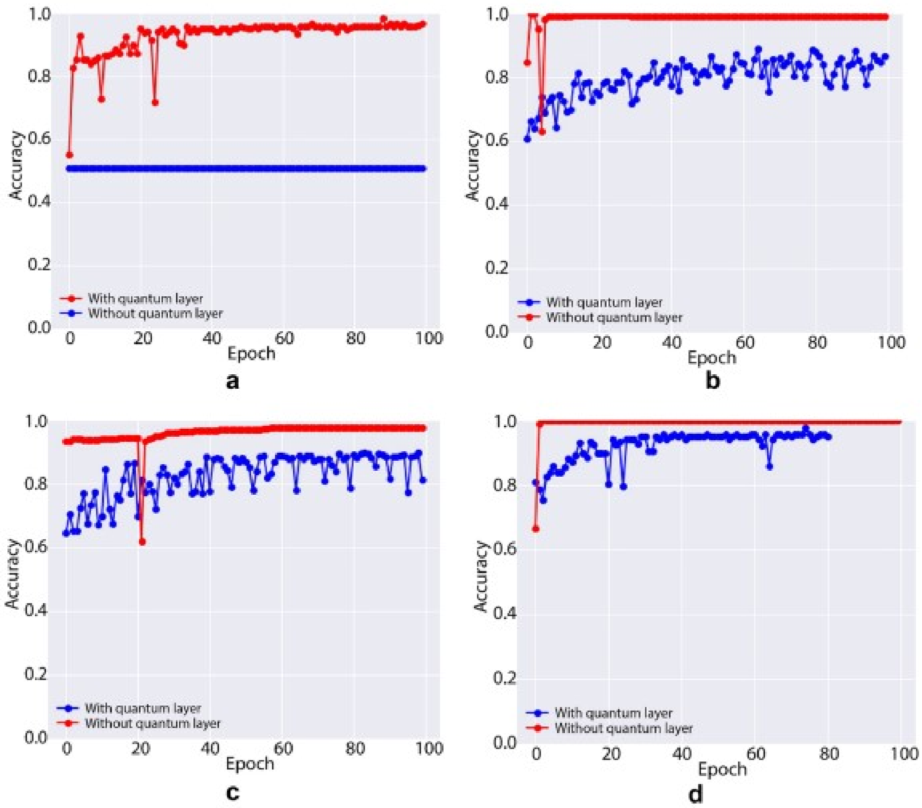

FIGURE 16. Classificationresults on CML and QNN model on 0.4 and 0.5 cross- validation: a., b Chinesedataset and on 0.4 and 0.5 cross-validation. C, d POF Hospital on 0.4 and 0.5cross-validation

UCSD-AI4H/COVID-CT					POF Hospital Pakistan				
Actual images		Synthetic images generated using CGAN		Total images Actual + synthetic	Actual images		Synthetic images generated using CGAN		Total images Actual + synthetic
Healthy slices	COVID-19 slices	Healthy slices	COVID-19 slices	Healthy slices: 406 + 406 = 812 Covid-19: 406 + 406 = 812	Healthy slices	COVID-19 slices	Healthy slices	COVID-19 slices	Healthy slices: 4127 + 4127 = 8251 Covid-19: 5421 + 5421 = 10,842
406	406	406	406		4127	5421	8254	10,842	

FIGURE 17. Dataset descriptions

Experimental outcomes manifested that QNN performed better on both datasets as compared to the CML.

8. Fake News Detection: Case Study III

Machine learning can be used to detect fake news in an efficient manner, according to numerous research. However, machine learning algorithms experience challenges with efficiency as dataset sizes increase. You can use quantum machine learning to solve this problem. Research has shown that quantum computing can be used to tackle issues that require a lot of computation, and quantum methods can speed up the same problems by an exponential or quadratic factor. In the case study provided in (Amin et al.) , we will be looking into a fake news detection system using the quantum k-nearest neighbors machine learning model (QKNN) with genectic and evolutionary feature selection (GEFeS) compare the performance with the traditional K-Nearest Neighbors model (KNN).

The procedure adapted for evaluation in (Kalinin and Krundyshev) is given in Fig. 18.

8.1. Dataset

The dataset used in (Rajashekhar, Pravin, and Thiruppathi) was chosen from BuzzFace, which contains 2282 news stories and postings that were gathered from Facebook during the 2016 US Presidential election. There are four categories for all articles and posts: mainly true, mostly false, mixed true and false, and no factual content. The "no fac-

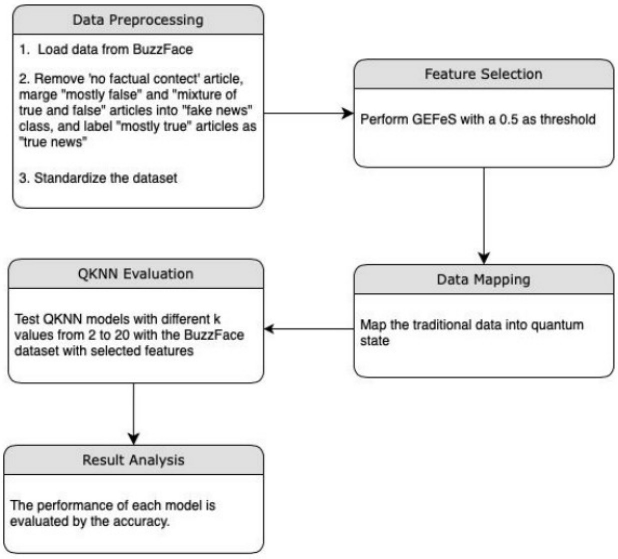

FIGURE 18. **The procedure adapted**

tual material" class of articles and posts are excluded from the dataset in this experiment. Additionally, the "mainly false" or "combination of true and false" articles or posts are combined into a single class termed "fake news," while the remaining data are designated as "real news." The dataset consists of 2018 articles and posts with 179 features after 264 articles and posts with the label "no factual material" were removed. The final dataset is divided into a training set (80%) and a testing set (20%).

8.2. Feature Selection

For feature selection, GEFeS is used with a threshold of 0.5. The feature masks are evolved using a steady state genetic algorithm every generation. Twenty randomly generated feature masks (FM) make up the initial population. The performance of an FM is assessed using the KNN model's accuracy. Each generation will produce a new FM to replace the FM with the lowest accuracy. The offspring is produced by mutation and crossover from two randomly chosen population members (Wesley, Quinn, and Mao) . The population of feature masks evolves and reflects optimum feature subsets after 1600 iterations of the method. A distinct K value is used for the KNN model inside the GEFeS method 19 times. There are 19 evolved populations of feature masks corresponding to the various k values utilised in the KNN model as a result of all GEFeS executions. The ideal person is chosen for each population, and the corresponding characteristic masks are kept. To construct GEFeS-reduced datasets for the various KNN K values, these feature masks are separately applied to the dataset.

8.3. Quantum Machine Learning

We evaluate the QKNN models using various k values from 2 to 20 with the corresponding GEFeS-reduced datasets in order to investigate the use of QKNN in fake news identification. We further decrease the dataset by using principal component analysis to transfer the data to the quantum space (PCA). Accuracy is used to gauge each QKNN model's performance (Branchi, Pereira, and Pirandola) .

Fig. 19 shows the results of the study for both the KNN model and the QKNN model with GEFeS. The variable quantity K value for each model is displayed on the x-axis, while the model correctness is displayed on the y-axis. In all K values, QKNN with GEFeS outperforms conventional KNN. As the K value rises, both models have a tendency to become more accurate. At most, QKNN with GEFeS outperforms the conventional KNN by 5%, and at the very least, by 0.029%. The data shown can also be used to determine the best K value for each model.

For the conventional KNN, the accuracy reaches its maximum at a value of 83.71% with a k value of 18. However, the accuracy of the QKNN using GEFeS peaks at 87.12% and k = 13. In relation to this problem, each of these peaks indicate the ideal k values for both the models.

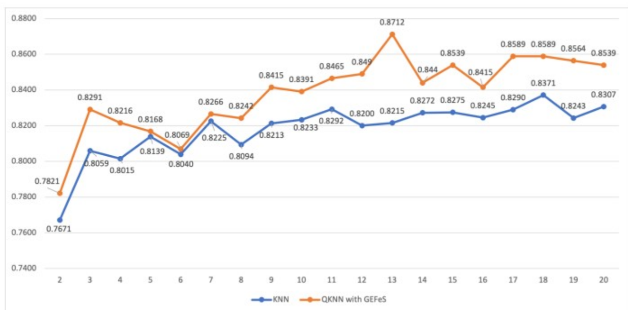

FIGURE 19. **The accuracy of KNN and QKNN with GERFeS**

In conclusion, the results show that for all values of K, the QKNN with GEFeS outperforms the conventional KNN. In Figure 20, the overall performance is shown. The average performance of the conventional KNN and QKNN with GEFeS across all k values is displayed in the following table. The

	KNN	QKNN with GEFeS
Avg	0.8179	0.8380

FIGURE 20. The Overall AverageAccuracy of the KNN and the QKNN with GERFeS

QKNN with GEFeS model performs on average 83.8% better than the traditional KNN model overall (81.79%). These show that the QKNN with GEFeS is a top performer on average.

9. Conclusion

In this investigation, our goal was to summarize the effects of quantum computing on machine learning. Although most of the research in these fields was mainly theoretical until recently, we now possess real quantum machine learning algorithms. As predicted, these algorithms surpass their traditional counterparts in terms of speed and efficiency. By combining machine learning with quantum computers, classical algorithms can frequently be executed at a much faster pace.

The potential influence of quantum computing on machine learning is enormous. As quantum computers with more qubits become available, we will be able to test more quantum algorithms, providing us with a complete understanding of the impact that quantum computers will have on machine learning.

Moreover, we explored three case studies on the application of QML and compared the outcomes with their classical counterparts. It is evident from the results that QML algorithms and methods provide faster, more efficient, and more accurate solutions in all three cases. This demonstrates the potential of quantum machine learning in real-world applications.

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