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Quantum Machine Learning : Scope for real-world problems

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Abstract

Quantum computing with its inherent parallelism provides a quantum advantage over classical computing. Its potential to offer breakthrough advances in various areas of science and engineering is foreseen. Machine learning is one of the key areas where the power of quantum computing can be utilized. Though many machine learning algorithms have been successfully developed to solve a variety of problems in the past decades, these algorithms take a long time to train. Also working on today's colossal datasets makes these algorithms computationally intensive. Quantum machine learning by utilizing the concepts of superposition and entanglement promises a solution to this problem. Quantum machine learning algorithms are in surface for the past few years and majority of the current research has dealt with the two machine learning problems namely classification and clustering. In this paper, a brief review of the recent techniques and algorithms of quantum machine learning and its scope in solving real world problems is studied.

Keywords: Quantum machine learning; Quantum algorithms; Quantum subroutines.

1. Introduction

The theoretical foundations of quantum computing were laid by Richard Feynman in his paper [1] where he discussed a computer that could simulate quantum physics and then the realization of how a quantum computer could be implemented was given by Ignacio Cirac and Peter Zoller in their paper [2] where they suggested that a quantum computer can be implemented by trapping cold ions and interacting them with laser beams. Since then, a lot of progress has been made in quantum hardware and in coming years a quantum computer of around 1000 qubits is aspired. In parallel to the progress in quantum hardware, quantum algorithms have also gained tremendous progress. Shor's Algorithm [3] and Grover's algorithm [4] have already shown the power of quantum algorithm by

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solving integer factorization problem and by speeding up search in unstructured databases, respectively. In the initial years only a handful of quantum algorithms for searching and factorization were developed but today various categories of quantum algorithms such as algebraic, optimization, approximation, search and machine learning are getting developed rapidly. Development of quantum algorithms for machine learning has aided the emergence of new field called the Quantum Machine Learning (QML).

Machine learning problems essentially comprises of two tasks: to efficiently handle massive amounts of data and to design algorithms that process this data in the fastest possible way. As far as the first task is concerned quantum registers can handle far more data than the classical registers. A n-classical bit register can only store n-size binary string whereas a n-qubit register can store 2^n n-size binary string by encoding the information in amplitudes. Although the extraction of all these strings is a tough task as the state collapses on measurement and in turn only one amplitude or one string is returned. But these qubits provide inherent parallelism so it is possible to write algorithms that can work on all these 2^n string parallelly and provide an exponential speedup over classical algorithms.

Essentially, QML is an amalgamation of Quantum computing and machine learning. This amalgamation of Quantum computing with machine learning can be carried out in four ways:

• The Classical-Classical approach (CC): In this approach the algorithms are classical but are influenced by the concepts of quantum mechanics, quantum processing or quantum information. These algorithms are called 'quantum inspired', are applied on classical data and run-on classical computers.

• The Classical-Quantum approach (CQ): In this approach quantum machine learning algorithms are applied on classical data to perform efficient machine learning tasks. Generally, here quantum translations of classical machine learning or existing quantum algorithms are sought that could efficiently carry machine learning tasks and provide quantum advantage over classical algorithms.

• The Quantum-Classical approach (QC): Here, classical machine learning methods/algorithms are applied to quantum data which facilitates the quantum computers to learn and get valuable insights from this data.

• The Quantum-Quantum approach (QQ): In this approach both the algorithm and the data are of quantum nature. In other words, the QML algorithms manipulate the quantum states in order to understand the underlying patterns and learn about the data.

Out of the four approaches the CQ and CC approaches are more explored in QML arena. Many papers employing Quantum inspired machine learning and Quantum Translations of machine learning algorithms have been in surface and shown remarkable results in the recent years.

Quantum inspired machine learning (based on CC Approach): Quantum inspired computing paradigm was first introduced in [5] by Moore and Narayan in 1995 where they discussed quantum inspired versions of selection sort and 15 puzzle problem. Since then, many optimization algorithms (quantum particle swarm optimization, quantum ant colony optimization, quantum fish swarm optimization etc.) inspired by quantum computing have been developed and utilized in varied domains [6], [7], [8]. Specifically, quantum genetic algorithms and quantum evolutionary algorithms have utilized quantum advantage more effectively as seen in [9], [10], [11], [12]. Quantum inspired Neural Networks (NNs) based on Quantum computing and multi-agent system was proposed by [13] which provided shorter training time due to powerful parallel processing capability. The recent work on quantum inspired NNs include application of quantum inspired differential algorithm for deep belief networks which improves global search ability and counters the premature convergence [14], designing a quantum inspired complex valued neural network for multimodal sentiment analysis that uses superposition and entanglement for interaction among modalities and achieves comparable results to current classical methods for sentimental analysis [15]. Although there are many merits of this quantum inspired approach for machine learning but the inconsistency in measurement sometimes poses a challenge. In future this challenge could be handled well and more quantum inspired versions of algorithms could come up leveraging the parallel processing capability of quantum algorithms.

Quantum Translations of machine learning algorithms (based on CQ approach): This approach to machine learning involves creation of quantum equivalents of standard machine learning algorithms and applying them to machine learning problems. The advantage of this approach is that it can provide exponential speedup as is shown in [16] where quantum k-means clustering is applied, also it provides more privacy as only exponentially small fraction of data gets analyzed thus enhancing data security. Many supervised and unsupervised classical machine learning algorithms like support vector machine [17], [18], [19], k nearest neighbor [20], [21], k-means clustering [22], [23], neural network classifiers [24], [25] have been translated into quantum versions. We will be discussing two of these algorithm QSVM and quantum k-means clustering in this paper.

Both of the above-mentioned approaches have been implemented to solve practical problems on smaller datasets. In [18] quantum support vector machine is implemented for classification over OCR and Iris datasets. The algorithm can be extended to all linearly separable datasets. In [14] quantum inspired algorithm is applied to fault detection problems which performs better in accuracy and speed, than the state-of-the-art classification algorithms and can be optimized for general detection problems. Although in its nascent state, QML is promising future potential in handling larger datasets and may become an alternative to classical machine learning.

The primary contribution of the paper is: we review the current QML algorithms and compare the different variants of notable QML algorithms, namely the quantum support vector machines, quantum k-means algorithm and quantum neural networks. Also, the scope of QML and its relevance in solving real-world problems is discussed. The paper is organized as follows: Techniques like fast Fourier transform (FFT) are widely used in machine learning (especially in Convolutional neural networks, feature extraction and dimensionality reduction), also many machine learning algorithms involve computation of eigen values and eigen vectors. FFT and eigen value / eigen vector computation have their quantum counterparts namely the quantum Fourier transform and quantum phase estimation algorithm which are used as subroutines in QML algorithms. We will be discussing them in Section 2. In Section 3 we discuss the quantum equivalents of support vector machines, k-means clustering and neural networks. Section 4 will be detailing the contribution of QML in the real-world problems.

2. Quantum Subroutines

2.1. Quantum Fourier Transform

Quantum Fourier transform (QFT) is essentially the quantum implementation of the classical discrete Fourier transform (DFT). The discrete Fourier transform has been a popular technique having wide applications in almost all science and engineering disciplines especially in the area of digital signal processing. The DFT transforms a discrete time domain representation to its frequency domain representation. Let x(n) be a signal containing 0,1,2. . ., N samples then its DFT can be given as

$$f(k) = \frac{1}{\sqrt{N}} \sum_{n=1}^{n-1} x(n) e^{\frac{-2\pi kn}{N}} \tag{1}$$

Generally, it can be said that DFT transforms one vector ($v_1, v_2, v_3, \ldots, v_n$) to another vector ($w_1, w_2, w_3, ., w_n$).

$$w_k = \frac{1}{\sqrt{N}} \sum_{n=1}^{n-1} v_n e^{\frac{-2\pi kn}{N}} \tag{2}$$

Quantum Fourier transform (QFT) gives an exponential speed up to the DFT. It transforms one n-qubit quantum state, $|x\rangle$ to another n-qubit quantum state $|y\rangle$. Let the basis states $|0\rangle, \ldots, |N\rangle$, $N=2^n$ be represented as $|b\rangle$ where b is given $b = b_1 2^{n-1} + b_2 2^{n-2} + b_3 2^{n-3} + \ldots\ldots + b_n 2^0$. Quantum Fourier operator acting on $|b\rangle$ and its effect on basis state $|i\rangle$ will be

$$|i\rangle = \frac{1}{\sqrt{N}} \sum_{n=1}^{n-1} x(n) e^{\frac{-2\pi kn}{N}} |b\rangle \tag{3}$$

The QFT can be given as

$$y_k = \frac{1}{\sqrt{N}} \sum_{n=1}^{n-1} x_n e^{\frac{-2\pi kn}{N}} \tag{4}$$

Quantum Fourier transform is used as a subroutine in many notable algorithms [3], [4], [26]. It is generally used for period finding and determining order. Improvements and enhancement to QFT has been proposed in [27], [28].

2.2. Quantum Phase Estimation Algorithm

Quantum phase estimation algorithm (PEA) is suitable for solving eigen value problems. It can effectively find the eigen values of a Hamiltonian matrix. Some modifications of PEA are proposed for non-Hamiltonian/Hermitian matrices in [29]. The idea behind conventional PEA is, let H be a Hamiltonian, then the phase factor can be generated by a unitary evolution $U = e^{(-iHt)}$ The computation of this phase gives eigenvalues of the Hamiltonian H. The algorithm proposed by [26] works in the following way, first Hadamard gates are applied to the qubits in input register, then the phase shift operator is applied k-times which transform the state to (5) and each time the output $\theta, 2\theta, \ldots, 2^{k-1}\theta$ is measured. These measurements are then used to calculate the phase of the matrix.

$$\frac{1}{\sqrt{2}}\left(|0\rangle + e^{i2\pi k\theta_n 2^{k-1}}|1\rangle\right) \tag{5}$$

Below is the representation of the steps discussed above.

$$\left|\varphi > \mapsto_H \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle\right)|\varphi\rangle \tag{6}$$

$$\mapsto_{\mathcal{U}^n} \frac{1}{\sqrt{2}}(|\mathbf{0}\rangle + |\mathbf{1}\rangle)|\boldsymbol{\varphi} >\otimes \boldsymbol{\mathcal{U}}|\boldsymbol{\varphi}\rangle \tag{7}$$

$$\mapsto \frac{1}{\sqrt{2}}(|\mathbf{0}\rangle|\boldsymbol{\varphi}\rangle + \boldsymbol{e^{2\pi i\theta_k}}|\mathbf{1}\rangle)|\boldsymbol{\varphi}\rangle) \tag{8}$$

$$\mapsto_{\mathcal{H}\otimes\mathrm{I}} \frac{1}{\sqrt{2}}\left(\frac{|\mathbf{0}\rangle + |\mathbf{1}\rangle}{\sqrt{2}}\right)|\boldsymbol{\varphi}\rangle + \frac{e^{2\pi i\theta_k}}{\sqrt{2}}\left(\frac{|\mathbf{0}\rangle - |\mathbf{1}\rangle}{\sqrt{2}}\right)|\boldsymbol{\varphi}\rangle \tag{9}$$

The Quantum phase estimation algorithm can also be implemented using inverse QFT and it improves the performance of PEA. Some papers which have modified and improved the PEA in recent years are [30], [31], [32] uses PEA to find polynomial roots.

2.3. HHL Algorithm

HHL in HHL algorithm stands for Harrow Hassidim and Llyod, the name of the authors who proposed this algorithm in 2009. This algorithm solved the quantum linear system problem (QLSP) which is equivalent to the classical linear system of equations $Ax = b$. A brief description of the algorithm is as follows:

Suppose we are given a matrix A and a vector b, HHL algorithm solves the equation $Ax = b$, here b is encoded into a quantum state $|b\rangle$ and given as input to the algorithm which then returns state $|x\rangle$ which essentially gives $x = A^{-1}b$.

An overview of the algorithm is given below as described in [33]. The HHL algorithm goes through three phases: In the first phase, a phase estimation module calculates the eigenvalues of A and stores them in a register. In the second phase, the inverse of the eigen values obtained are computed by a unitary operation and controlled Ry rotations, then this result is encoded into ancilla qubit. In the third phase un-computation of the phase estimation and unitary operation is done and the ancilla qubit is measured. After measurement if the obtained result is 1, it means that the quantum state is approximate to $A^{-1}b$.

HHL algorithm is an important algorithm and is used in many QML algorithm as a subroutine. It helps in executing mathematical tasks that involve solving differential equations, matrix inversion, curve fitting etc., but it does not give the complete solution like the standard system of linear equations does. This is a drawback of HHL, although when used as subroutine, approximate solutions are better off and can be considered. Majority of the algorithms are concerned with partial solutions and therefore its utility is observed in such QML algorithms.

3. QML Algorithms

Machine learning is generally classified into supervised learning, unsupervised learning and reinforcement learning. In the first two learning the model or algorithm learns through analyzing the data whereas in reinforcement learning the model learns through interaction. In supervised learning the labelled data is given, that is, the input-output pair are provided. The machine learns by deducing the relationship between these pairs. In unsupervised learning the data is not labelled, that is, only the input data is provided. The machine learns by finding the structure from the data. Two QML algorithms quantum support vector machine (translation of support vector machine) and quantum k-means algorithm (translation of classical k-means algorithm) belonging to supervised and unsupervised machine learning respectively are discussed in this section.

3.1. Quantum Support vector machine (QSVM)

The Support vector machines (SVM) are widely used in classification problems. Classification is one of the concepts of supervised learning, where the goal is to predict the most likely predefined class to which the newly unseen data belongs, based on the number of predefined classes, the classification is termed as binary or multi-class classification. SVM works by finding an optimal hyperplane that separates the classes. The hyperplane focuses on the boundary data points and these data points are called support vectors. Let there be N training data points $p_1, p_2, p_3, ...p_n$ and two classes with label +1 and -1, then the labelled training data can be written as (p_i, l_i), $l_i \in \{+1, -1\}$. The equation of the hyperplane can then be given as $f(p) = w.p + b$, where w is the vector and b is the bias. To find this hyperplane w and b should be adjusted such that $l_i(w.p(i) + b) \geq 1$ for class +1 and $l_i(w.p(i) + b) \leq 1$ for class −1, concisely both equations can be written as $l_i(w.p(i) + b) \geq 1$. Many hyperplanes may satisfy the equation but the hyperplane that maximizes the margin (which is given by $2 / || w||$) is the optimal separating hyperplane. Many methods like Lagrange's can be used to find this maximum margin optimal separating hyperplane.

QSVM can be implemented in 2 ways, one approach uses Grover's search [34] wherein the maximum search is conducted on all possible solutions that are generated to find the hyperplane. This approach obtains a quadratic speedup. The other approach which provides exponential speedup [17] uses the HHL algorithm. The original quadratic programming problem is converted into linear system of equations problem which is solved using HHL.

Various enhancements to the QSVM have been proposed in literature. A summarized comparison among the recent variants of QSVMs is provided in Table 1. It can be seen that all the quantum versions give an exponential speed-up over classical SVM. In [18] an implementation of the QSVM on noisy intermediate scale quantum computers (NISQ) is proposed which uses an optimized HHL quantum circuit with reduced circuit depth that produces more accurate results on current NISQ. Although it has some drawbacks like it only classifies linearly separable datasets but it shows that QML algorithms like SVM can be run on NISQ computers efficiently. Also, QSVM on a four-bit quantum processor to solve optical character recognition trained with characters '6' and '9' is demonstrated in [35]. Further, in [36] kernel based QSVMs on DW2000Q quantum annealer are implemented and it suggests that the capabilities of future quantum annealers may be suitable for hard problems or problems where less training data is available. Hybrid quantum classical versions of SVM are discussed in [37] which suggests that difficult machine learning tasks can be tackled with classical intractable quantum feature map and thus enhance performance.

With the progress in quantum computer technology in future QSVMs may be effective in applications like pattern classification, handwriting recognition on large datasets with comparable accuracy.

Table 1. Summarized Comparison among the variants of QSVM algorithms

Algorithm	**Approach**	**State Preparation scheme**	**Kernel function**	**Speed-up**	**Complexity**	**Performance**	**Implementation**
Improved QSVM [17]	Hamiltonian simulation and matrix-inversion based	QRAM	Nonlinear	Exponential	Poly-logarithmic	Accuracy 0.9514	Qiskit python library
QSVM [18]	HHL algorithm based	Linear mapping	Linear	Exponential	-	Accuracy 99:5% (OCR) 98% (Iris)	Qiskit python library, pyQuil

HVQ-SVM [37]	Hybrid variables based	QPCA and QSVT	Nonlinear	Exponential	Poly-logarithmic	N.I.	N.I.
QSLS-SVM [37]	Hybrid variables approach and classical matrix inversion based	QPCA and QSVT	Nonlinear	Exponential	Polynomial	N.I.	N.I.

Abbreviations- QSVM: Quantum Support Vector Machine, HVQ-SVM: Hybrid Variable Quantum Support Vector Machine, QSLS-SVM: Quantum Sparse Least Square Support Vector Machine, QRAM: Quantum Random Access Memory, QPCA: Quantum Principal Component Analysis, QSVT: Quantum Singular Value Threshold, OCR: Optical Character Recognition, N.I.: No Implementation (either no implementation or details not given)

3.2. Quantum k-means algorithm

The classical k-means algorithm is one of the widely used clustering algorithms. Clustering is an unsupervised machine learning technique where in the data is grouped into classes or groups (clusters) or patterns that are determined by analyzing the structure of input data. The goal here is to find similarity in the data and group similar datapoints together into a cluster. Mathematically the clustering problem can be represented as below Let P = $\{P_1, P_2, P_3, ..., P_n\}$ be the data-set containing datapoints. A set of distinct clusters C can be defined as C = $\{C_1, C_2, C_3, ..., C_k\}$, where Ci refers to i[th] cluster and $C_i \neq \Phi$, subject to satisfying the conditions: and similarity (P_i, P_j) > similarity (P_i, P_k) where $P_i, P_j \in C_n$ and $P_k \neq C_n$. The similarity function depends on the metric used by the particular algorithm. The intra-cluster similarity needs be maximized, while the inter-cluster similarity be minimized for an optimum classification.

The classical k-means algorithm classifies data into k clusters, the datapoints are assigned to the nearest centroid in each iteration and calculation of new centroid is done by averaging the datapoints in the individual cluster, the iterations continue till there are no changes in cluster assignments. The quantum version of the k-means algorithm provides an exponential speedup over the classical k-means algorithm [38]. In Quantum k-means algorithm after the initial state is prepared, the similarity between datapoint and cluster centroid is calculated by finding the Euclidean distance from datapoint to each cluster centroid, generally, swap-test procedure is used as a subroutine for finding the distance and then the closest centroid is selected using Grover's optimization [39]. The cluster centroids are recalculated till convergence is achieved. Below are the details of the algorithm discussed above:

Swap test subroutine

Initialize the states $|x\rangle$ and $|y\rangle$ and the control qubit $|0\rangle$

$$|\varphi\rangle = |0, a, b\rangle \tag{10}$$

$$\mapsto_H \frac{1}{\sqrt{2}}(|0, a, b\rangle + |1, a, b\rangle) \tag{11}$$

$$\mapsto_{SWAP} \frac{1}{\sqrt{2}}(|0, a, b\rangle + |1, b, a\rangle) \tag{12}$$

$$\mapsto_H \frac{1}{2}|0\rangle(|a, b\rangle + |b, a\rangle) + \frac{1}{2}|0\rangle(|a, b > - |b, a\rangle) \tag{13}$$

Measure the control qubit if measurement probability is 1 then the states are identical and measurement probability is 0.5 then states are orthogonal

$$P(|0\rangle) = \frac{1}{2} + |\langle a|b\rangle|^2 \tag{14}$$

Distance calculation

Encode the data into quantum state and initialize the states as

$$|\varphi\rangle = \frac{1}{\sqrt{2}}(|0, a\rangle + |1, b\rangle) \tag{15}$$

$$|\psi\rangle = \frac{1}{\sqrt{2}}(|a||0\rangle + |b||1\rangle) \tag{16}$$

$$Z = |a|^2 + |b|^2 \tag{17}$$

Calculate similarity between $|\varphi\rangle$ *and* $|\psi\rangle$ using Swap test subroutine and calculate the distance

$$|a-b|^2 = 2Z\,|\langle\varphi|\psi\rangle|^2 \tag{18}$$

Use the Grover's Optimization and repeat the whole procedure till convergence is reached.

Several variations of quantum k-means algorithm and quantum inspired k-means algorithms have been seen in recent years. Table 2 compares three of these variations of quantum k-means algorithms. In [40] a quantum inspired k-means algorithm based on matrix product state (MPS) is proposed which promises higher prediction accuracy and is less susceptible to local minima trapping. Here the quantum state is represented using matrix product states and variational MPS sweeps are used. In [41] quantum k-means algorithm based on trusted servers in quantum cloud computing is used. Here the idea is to reduce the complicated quantum calculations and to reduce the number of times superimposition de-superimposition of quantum states occurs using quantum cloud server. In [42] quantum inspired ant lion optimized k-means algorithm is used for intrusion detection on KDD Cup 99 dataset which shows detection rate and accuracy is better than the classical k-means algorithm. Overall, it can be said that with the improvement in quantum hardware, these algorithms would certainly provide quantum advantage and in the future more efficient clustering algorithms would be designed that can surpass the classical classification algorithms in terms of time-complexity.

Table 2. Summarized Comparison among the variants of Quantum k-means algorithms

Algorithm	**Approach**	**Dataset**	**Performance**
Quantum inspired k-means [40]	Matrix Product States based	Yeast, E-coli	+3 to +5% increase in accuracy over classical k- means algorithm
Quantum k-means algorithm based on quantum cloud computing [41]	Swap-Test and GroverOptim based	-	Complexity reduced from O(MNkt) to O(M log N$\sqrt{k}$t)
OALO-K [42]	Ant Lion Optimization based	KDD Cup 99 dataset	98% accuracy

Abbreviations- QALO-K: Quantum-inspired Ant Lion Optimized hybrid k-means algorithm, KDD: Knowledge Discovery and Data mining, M: scale of vector, N: dimension of vector, k: clustering centres, t: number of iterations

3.3. Quantum Neural Networks

An artificial neural network (ANN) is an interconnection of artificial neurons, that mimics the working of biological neurons and are used in information processing. The simplest ANN model is the perceptron, there is a layer of input neurons $n_1, n_2, n_3 \ldots, n_m$ and with each neuron a weight (analogous to the synapses in biological neurons) is associated $w_1, w_2, w_3, \ldots, w_n$ the output neuron fires when the $\sum_0^m n_i w_i$ exceeds a specific threshold θ, this can be expressed in equation as:

$$f(x) = \begin{cases} 0, \; if \; \sum_0^m n_i\, w_i \leq \theta \\ 1, \; else \end{cases} \tag{19}$$

This function f(x) is called the activation function.

Multilayer ANNs with hidden layers which adds nonlinearity are widely used in machine learning. Training these neural networks requires gradual updates to the weights till the desired result are obtained, for example in case of supervised learning the difference between actual output and desired output can be used for weight updates.

Some complex ANNs like the convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory networks (LSTM) and generative adversarial neural networks (GAN) etc. have increased the power of ANNs significantly, but on the cost of increased complexity. As the number of layers, interlayer connectivity and number of neurons increases, the complexity also increases which hinders the efficiency and training time of the model. Although there are methods to optimize the performance but for the massive data that is getting generated, eventually in future a paradigm change would be needed and quantum computing could be the change and the quantum neural networks (QNN) an alternative.

The basic unit of QNN is the quantum neuron which can be thought of as a quantum version of artificial neuron. The input to neuron is a quantum state with an amplitude and phase. The weights encoded in amplitude may be complex valued and the output will again be a quantum state. A perceptron equivalent can then be defined as:

$$|y\rangle = U \sum_{n=0}^{n-1} w_{ny} \ |x_n\rangle \tag{20}$$

where U is the activation function given by an arbitrary operator and w_{ny} are the weights. Training of the perceptron can be achieved by the learning rule described in [43].

$$w_{iy}(t+1) = w_{iy}(t) + \eta(|d\rangle - |y\rangle)\ \langle x_i| \tag{21}$$

where d is the target state, y is the state of neuron at time t and η is the learning rate.

QNNs with different approaches have been designed in recent years. Table 3 provides a comparison of some quantum and quantum-inspired neural networks. In [43] a quantum model of perceptron is successfully implemented in near-term quantum hardware which provides exponential advantage over the classical perceptron. In [44] QNN for solving pattern using an improved multi-layer activation function is tested for lie detection data and better detection rate are observed. In [45] Quantum convolutional neural network (QCNN) is used to extract feature through decentralized speech processing, the model is able to show stable performance and competitive results when compared to classical NNs. Overall, the QNNs are promising great advantage over classical approaches but still a comprehensive QNN approach that can provide a real quantum advantage is yet to be discovered.

In this section the QML algorithms and their variants were discussed. It can be inferred that QML algorithms irrespective of whether they are implemented on real quantum computer or run on simulations, they have outpaced their classical counterparts. Figure 1 depicts the same inference (the accuracy of each QML algorithm is better than the classical one). Also, it should be noted that the algorithms that are implemented on quantum computers, are of limited capability. With the increase in capacity (1000 qubit quantum computer), it would be possible to apply QML to larger datasets and to quantum supremacy in machine learning domain.

Table 3. Summarized Comparison among the different QNNs

Algorithm	Approach	Application Area	Training Scheme	Performance	Implementation
Quantum Perceptron [43]	HSGS based	Pattern Recognition	Perceptron update rule	-	Qiskit python library
QNN [45]	Multi-layer activation function based	Lie Detection	Levenberg-Marquardt Algorithm based	84% to 95% Detection rate	MATLAB
QCNN [46]	Variational Quantum Circuit	Privacy Preservation, Speech Recognition	-	95.12% Accuracy	Qiskit python library, PennyLane

Abbreviations- HSGS: hypergraph states generation subroutine, QNN: Quantum Neural Network, QCNN: Quantum Convolutional Neural Network,

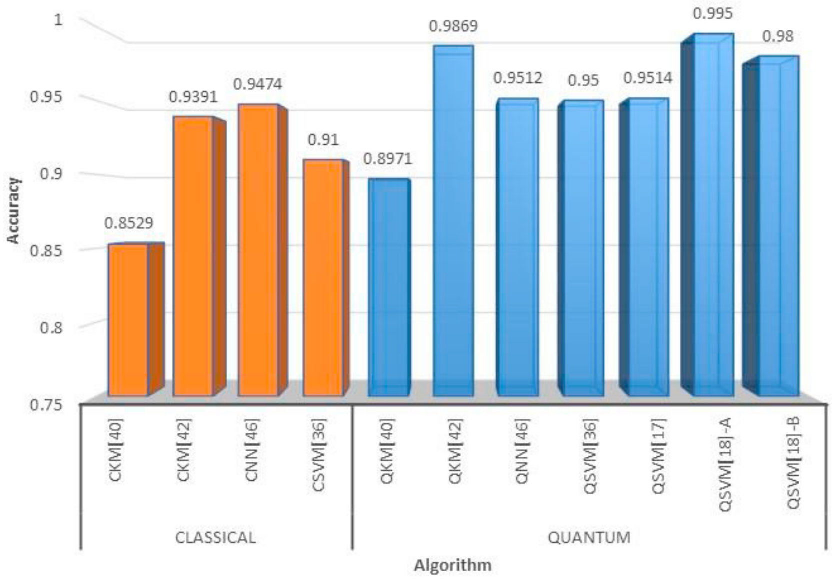

Figure 1. Accuracy comparison of classical and quantum algorithms. Abbreviations: CKM denotes Classical k-means algorithm, CSVM denotes Classical Support Vector Machines, CNN denotes Classical Neural Networks, QKM denotes Quantum k-means algorithm, QSVM denotes Quantum Support Vector Machines, QNN denotes Quantum Neural Networks

4. Applications of QML in real world problems

In this section we will be discussing problems where QML has an advantage over the classical machine learning algorithms. Table 4 shows the solutions proposed by various authors for solving some of the NP & P class problems through QML techniques. The table shows that QML is applied in many domains like communication networks, privacy preservation, bioinformatics, computational biology, particle physics, natural language processing, image processing and many more. It is seen that pattern classification and pattern recognition problems have been dealt well by QML algorithms, especially techniques like amplitude amplification, provide a good trade-off over classical approaches in terms of time complexity. The Quantum associative memory based on quantum pattern recognition is one application that may solve the storage and state preparation problem that is faced by many quantum algorithms. Image processing is another problem where significant work has been done and quantum Boolean image processing and quantum state tomography techniques promise to be an alternative to practical image processing. Natural language processing is another problem which is practically solved on NISQ computers for small datasets. The most important breakthrough of QML will be to be able to solve the biological and bioinformatics problems like protein structure prediction, protein binding, gene expression and drug design. Parallel computation of protein and DNA sequences through superposition may provide a solution to these problems but optimum quantum algorithms are needed to fully utilize this potential as measurement collapses the advantages provided by superposition. Further the domain of communication networks and privacy preservation has also been touched by QML and significant work done.

Although QML has touched upon various domains of science and engineering, but still it is in its nascent stage. Presently, the noise in quantum hardware limits the use of QML for real world scenarios. In the coming years, with the advances in quantum technology may overcome the limitations faced by current QML algorithms.

Table 4. QML applications in real world

Problem	**Paper**	**Brief Description**	**Limitations**
Pattern recognition	Quantum Pattern Recognition[47]	Quantum Associative memory based on pattern recognition is proposed. Information retrieval is probabilistic in nature. Storage algorithm and retrieval algorithm uses concepts of quantum rotations and amplitude amplification. State- dependent cloning is used for remembering stored patterns.	The identification efficiency cannot be tuned or influenced in the quantum associative memory proposed.
Pattern Classification	Quantum Computing for Pattern Classification[48]	A quantum k nearest neighbour algorithm (kNN) algorithm is proposed which gives advantage in terms of time complexity over classical kNN. Further it is shown that the probabilistic output of quantum algorithm gives additional information that helps judgement in classification tasks	Overall classification efficiency is low and the algorithm doesn't work for continuous inputs
Pattern Classification	Quantum decision tree classifier[49]	A quantum decision tree classifier is designed. Training states have multiple copies is assumed and quantum entropy impurity measure is used as criterion for selecting nodes in making decision tree.	The approach doesn't handle the problem of missing attributes values and training data with quantum noise.
Image Processing	Quantum realization of the nearest neighbor value interpolation method for INEQR[50]	A practically significant quantum image scaling algorithm using nearest neighbor value interpolation is proposed.	Quantum circuit used can be optimized in terms of complexity and model can be generalized for all-scale ratios.
Wireless Communication networks	Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future[51]	A quantum computing assisted machine learning and QML based framework for 6G communication networks has been proposed	Multi access based on QML can be improved for massive connectivity and best network resource utilization
Statistical disclosure control	Privacy-preserving quantum machine learning using differential privacy[52]	A quantum logistic regression is tested on a discrete laplace noise (applied on input unit to ensure privacy preservation) transformed dataset	Objective and output perturbation for privacy preservation can be explored for in- creasing accuracy.
Transcription factor DNA-binding(TF-DNA binding)	Quantum annealing versus classical machine learning applied to a simplified computational biology problem[53]	A quantum annealing based algorithm is used to solve TF-DNA binding problem by using quadratic unconstrained binary optimization (QUBO) approach and compared with the classical counterparts	Discrete weights are used which are not favorable for large datasets.

Natural language Processing (NLP)	QNLP in Practice: Running Compositional Models of Meaning on a Quantum Computer[54]	NLP tasks are implemented on Noisy intermediate-scale quantum (NISQ) computer using DisCoCat framework and two NLP models for simple sentences were proposed	The problem of scalability when the size of vocabulary increases is an issue for designing real world QNLP framework
Protein-structure prediction	Protein structure prediction using AI and quantum computers[55]	A quantum hybrid deep neural network is trained on CASP dataset to predict protein structure successfully.	Not suitable for large datasets
Collider phenomenology	Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier[56]	A novel hybrid neural network based on variational quantum classifier is used, which differentiates between signal and background comparably well than classical neural networks	The suitability of VQC for larger datasets limits this hybrid approach's applicability
Reinforcement Learning	Reinforcement Learning with Quantum Variational Circuit[57]	Hybrid and pure quantum variational circuits in Deep Q-Networks algorithm applied on Cart- Pole and Blackjack environment are proposed and two encoding schemes scaled encoding and directional encoding are introduced.	Potential for increasing the generalizability both through encoding schemes and varying hyperparameters of QVC can be realized further.

5. Conclusion

Quantum machine learning promises break-through advantage in the field of machine learning. With the tremendous amount of data getting generated and technological advents in the recent years, the probabilistic and optimization based classical machine learning algorithms may find it difficult to provide solution to real world problems. QML based on quantum computing concepts of superposition and entanglement are best suited for future ML problems. Quantum subroutines like QFT, PEA and HHL are fine-tuned by researchers for problem specific solutions. Many modifications and optimized versions (in terms of circuit complexity) of these subroutines have already shown their potential on NISQ devices. Quantum Variational Classifier, Quantum Decision tree, classifiers based on quantum annealing have been used over smaller datasets offering the quantum advantage over classical algorithms. In this paper we have tried to give an overview of QML and discussed how QML algorithms achieve exponential speed-up over their classical counterparts both in terms of performance and in capacity to store information. It may seem that these algorithms can replace the classical algorithms completely but there are challenges that need to be dealt before we can acknowledge quantum supremacy. The first challenge is the state preparation. To convert the classical data into quantum data, though amplitude encoding in state preparation requires a smaller number of qubits but the time to prepare data may somehow nullify the speed-up provided by the algorithms. The QRAM address these issues but still it is not a suitable technology for repeatedly preparing data for QML. The second challenge is the limitations of the current near-term devices, the algorithms are needed to be optimized in terms of circuit depth to nullify the effect of decoherence. Implementing QML for computationally exhaustive applications using large dataset is still not possible on current devices. With the progress in quantum hardware and design of fault tolerant quantum systems, in future this may not be a challenge. However, the way to practical quantum machine learning has already been paved off, implementations of QSVMs, Quantum classifiers and QNNs as discussed in this paper give a glimpse of how future QML algorithms may help in solving optimization and decision-making problems.

Overall QML has shown its presence in diverse fields ranging from healthcare, networking, privacy preservation, IoT, etc., but if we gauge the current impact of the research in solving real-life problems, it is still in its infancy. Recognizing a few handwritten digits using NISQ computers may be considered an important achievement in an experimental setup, but real-word handwriting recognition would require improvements in both the quantum algorithms domain and the quantum hardware domain. The capability of quantum hardware is increasing at a steady rate, and possibility of a thousand bit quantum computer is certain. QML algorithms are also being developed at a rapid rate but designing an optimized quantum algorithm in terms of circuit complexity and depth for current NISQ devices is still a challenging task. Thus, it can be said that the potential that QML has shown in solving real-world problems could soon be realised. These are open research problems and good research directions for researchers working in machine learning domain.

Future direction : QML is best suited specifically for text and image classification problems on smaller datasets. In future we would like to explore these problems with a pure quantum perspective and translate some of the classical machine learning algorithms for text classification.

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