



International Research Journal Of Modernization in Engineering Technology and Science

(Peer-Reviewed, Open Access, Fully Refereed International Journal)

e-ISSN: 2582-5208

Ref: IRJMETS/Certificate/Volume 3/Issue 11/31100030799

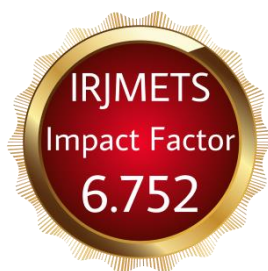
Date: 23/11/2021

Certificate of Publication

This is to be certify that author “Aryaman Singh” with paper ID “IRJMETS31100030799” has published a paper entitled “MACHINE LEARNING IN QUANTUM PHYSICS” in International Research Journal Of Modernization In Engineering Technology And Science (IRJMETS), Volume 3, Issue 11, November 2021

A. Deyshi

Editor in Chief



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MACHINE LEARNING IN QUANTUM PHYSICS

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ABSTRACT

Machine learning could also be a significant application of quantum computing in the coming years, but challenges remain as near-term devices have a limited number of physical qubits and high error rates. Also, the topic of quantum computing brings together ideas from classical scientific theory, computing, and physics. It, therefore, features a fundamentally important role within the science of physics. However, the mathematical treatment of data, especially information science, is recent, dating from the mid-1900s. This has meant that the full significance of data as a fundamental concept in physics is merely now being discovered. Through this research article, we aim to highlight the machine learning aspects of quantum physics.

I. INTRODUCTION

Machine learning concepts aim to design artificial intelligence models that learn from previous experience, human or otherwise, without being explicitly formulated for the task. Machine learning applications are paramount, including predicting the future, recognizing patterns, trends and making decisions. These models can handle sizable quantities of data in the form of large vectors, matrices, and tensors. Supported by increasing computing power and algorithmic advances, machine learning techniques have become irreplaceable tools for finding patterns in data. Quantum systems produce designs that classical methods can not make efficiently, so it is reasonable to conclude that quantum computers may outperform classical computers on machine learning tasks.

II. WHAT IS MACHINE LEARNING?

Machine learning could also be a subfield of calculating concerned with assembling algorithms that, to be valid, believe a group of samples of some phenomenon. These illustrations can come from nature, be handcrafted by humans, or be generated by another algorithm.

2.1. TYPES OF MACHINE LEARNING

The topic of Machine Learning varies between supervised, semi-supervised, unsupervised, and reinforcement.

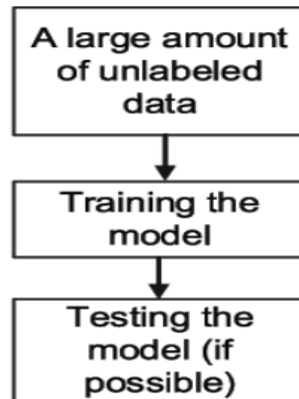
2.2.1 SUPERVISED LEARNING

A supervised machine learning algorithm aims to use the dataset to produce a model that takes a feature vector x as input and outputs information that allows deducing the label for this feature vector.



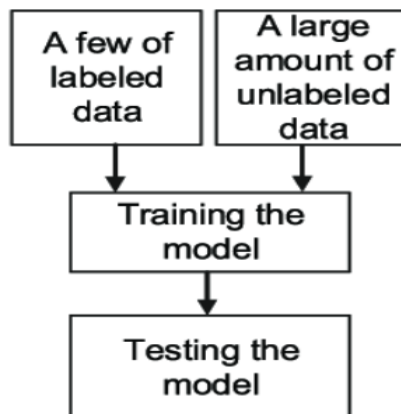
2.2.2 UNSUPERVISED LEARNING

Unsupervised learning uses algorithms from ML to study and cluster unlabeled datasets. These algorithms discover data groupings or hidden patterns without the need for human intervention.



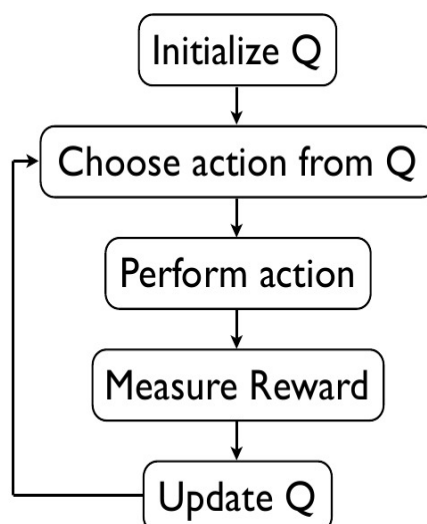
2.2.3 SEMI-SUPERVISED LEARNING

Semi-supervised machine learning may be a combination of supervised and unsupervised machine learning methods.



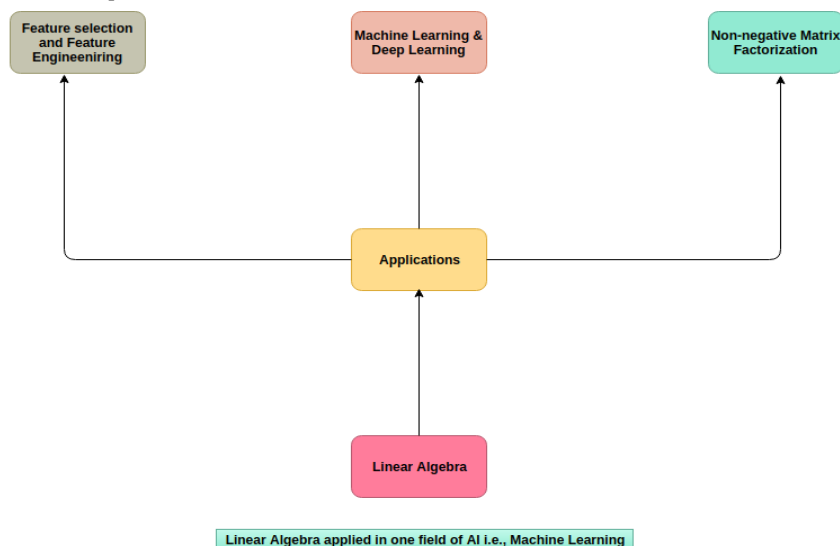
2.2.4 REINFORCEMENT LEARNING

Reinforcement learning may be a machine learning training method supporting rewarding desired behaviors and/or punishing undesired ones. A reinforcement learning agent can generally evaluate and interpret its environment, take actions accordingly, and learn through trial and error.



III. LINEAR-ALGEBRA BASED QUANTUM MACHINE LEARNING

A wide sort of data analysis and machine learning protocols operate by performing matrix operations on vectors during a high dimensional vector space. But quantum physics is all about matrix operations on vectors in high dimensional vector spaces.



The critical methodology behind these methods is that the quantum state of n qubits is a vector in a 2^n -dimensional complex vector space; quantum logic operations or measurements performed on qubits multiply the corresponding state vector by $2^n \times 2^n$ matrices. By building up such matrix transformations, quantum computers have been shown to perform joint linear algebraic operations such as Fourier transforms, finding eigenvectors and eigenvalues, and solving linear sets of equations over 2^n -dimensional vector spaces in time polynomial in n , exponentially faster than their best known classical counterparts.

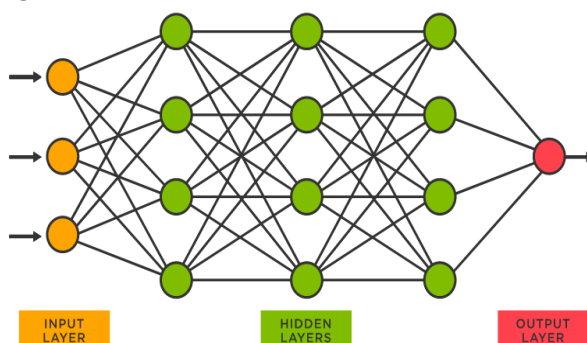
IV. QUANTUM MACHINE LEARNING ALGORITHMS

Most quantum machine learning algorithms are formulated on classical algorithms while utilizing quantum concepts such as entanglement and superposition. This paper will look at the hierarchy of quantum machine learning algorithms as Supervised, Semi-Supervised, and Unsupervised for classifying different algorithms.

4.1 SUPERVISED ALGORITHMS

Quantum Neural Network (QNN) is one of the prime examples of a supervised quantum machine learning algorithm. As an early approach in this field, Narayanan and Menneer [7] showed the theoretical form of a QNN architecture and how the components of such a system would perform compared to classical counterparts. Although their work is a high-level description of the parts needed, it laid the foundation for future implementations of QNN.

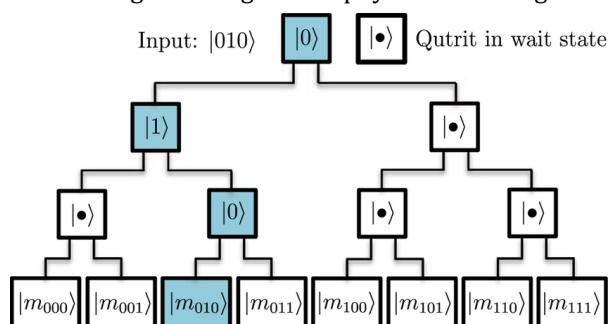
Artificial Neural Networks (ANNs) are based on an aggregation of non-linear functions applied to neurons that are laid out in layers and sequences. The linear nature of quantum mechanics, however, implements non-linear activation functions challenging.



Ricks and Ventura [8] proposed an algorithm for training quantum-based neural networks capable of producing high accuracy solutions. Their approach uses a minimum set of entangled qubits to hide the training data set and may return results that encompass a predetermined portion of the training data.

Like classical computers, the training and learning of a QNN rely on quantum memory. Achieving a Quantum Random Access Memory (QRAM) independent of the classical counterparts has been an intersection of quantum computing and neural networks.

Oliveira [9] introduced a quantized equivalent for RAM-based Neural Networks (RbNNs) that debuted as quantum RAM-based Neural Networks (q-RbNN). The main advantage of q-RbNNs is their ability to use the classical learning algorithms while taking advantage of the physical advantages of quantum-based machines



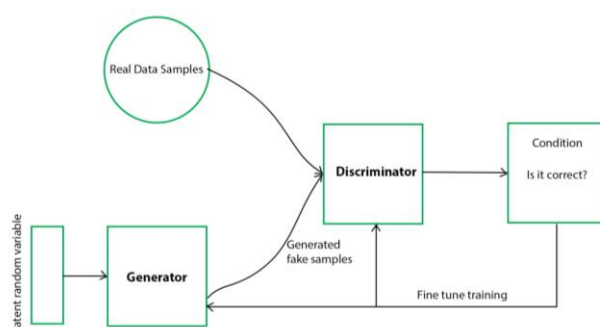
4.2 SEMI-SUPERVISED ALGORITHMS

Semi-supervised quantum algorithms are often viewed as optimization algorithms, quantum-enhanced Reinforcement Learning (RL), and generative models.

Although researchers have examined ways that Artificial Intelligence (AI) can benefit from Quantum Information Processing (QIP) in supervised and unsupervised learning rather exhaustively, RL remains an area that needs to be explored. Learning from experience may be a defining signature of an intelligent agent, artificial or otherwise.

McKiernan et al. [11] defined a framework for using RL to improve hybrid quantum-classical computing. The framework has a learning environment where the state, action, and rewards are decided on the problem.

Generative Adversarial Network (GAN) [12] is a subset of ML where two networks compete and generate new data based on the observed training data. Wasserstein GANs (WGAN) may be a variation of such networks that uses Wasserstein distance to work out the space between the particular and generated distributions and is optimistic for improving the training stability of GANs due to the continuity and smoothness.



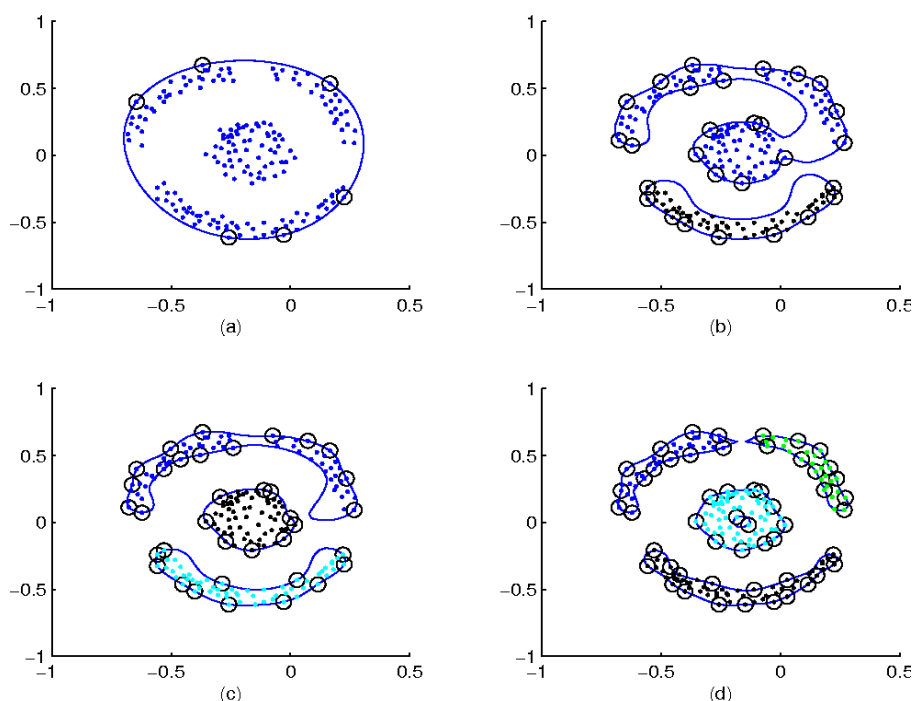
4.3 UNSUPERVISED ALGORITHMS

Clustering algorithms and Dimensionality reduction are the basic examples of unsupervised quantum ML algorithms. Classical algorithms take polynomial time in vector number and dimension to solve these problems, while QML algorithms take logarithmic time in both, thus achieving exponential speedup. The amount of information $O(\log MN)$ that needs to be accessed for QML operations, compared to the size of information $O(\log MN)$ being applied to classical machine learning, means that the privacy of that data is also increased by the use of QML over classical ML.

Aïmeur et al. [10] have described three quantum algorithms that could be substituted for components of classical algorithms and achieve exponential speedup in clustering over classical algorithms; their quantization presupposes the existence of a black-box quantum circuit which acts as a distance oracle, giving the distance between vector inputs. Such assumptions may not be valid or available readily but their subroutines can be followed, respectively.

- To find the two most distant points from one another in a vector dataset.
- To find the n closest points to another, specified point, all in a vector dataset.
- To produce neighborhood graphs of vector datasets, all in times superior to classical counterparts.

Support Vector Clustering (SVC) correlates data points with states in Hilbert space. These states are represented by Gaussian wave functions and can allow for the weighting of specific issues to give them more emphasis, presumably as cluster center possibilities. This is valuable if one has a method, such as SVC, unduly influenced by outliers.



V. CONCLUSION

To explain the mixture of quantum computing and machine learning, we must express quantum computing in terms that do not unnecessarily hide the role of programming. Quantum computers' famous success story is the factoring of huge numbers. The chance for quantum machine learning is going to be in learning many simple lessons— concepts which will make society more efficient, not just the complex problems currently attracting geniuses and armies of researchers.

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