

A Comprehensive Review of Quantum Machine Learning Algorithms and Their Applications in Solving Real-World Computational Challenges

Mohana Priya T¹, Abdalla Ibrahim Abdalla Musa², Poorana Senthilkumar S³, Abdalnaser Rashid⁴, Thirunavukkarasu V⁵, Rajesh Kanna R⁶

^{1,5,6}Department of Computer Science, CHRIST University, Bangalore, India

^{2,4} Department of Computer Science, College of Computer, Qassim University, Saudi Arabia

³Department of Computer Applications, Dr N.G.P. Arts and Science College, Coimbatore, India

Abstract

Quantum Machine Learning is a subfield of quantum computing that focuses on applying machine learning techniques to quantum algorithms and quantum systems. Quantum machine learning is an active area of research, with many scientists and engineers exploring its potential for solving complex problems. The goal of quantum machine learning is to explore the unique features of quantum systems that can be used to solve problems that are intractable for classical machine learning algorithms. Quantum algorithms can offer significant speedups over classical algorithms in certain cases, and this property can be leveraged in machine learning algorithms to achieve faster training and improved accuracy. In this research paper, a brief review of the recent techniques and algorithms of quantum machine learning and its scope in solving real world problem are analysed.

Keywords: Quantum Computing, Quantum Algorithms, Quantum Machine Learning, IBM Quantum Lab

Introduction

Nowadays quantum computing is the intersection of physics and engineering. Until recently, this form of computing was basically a hypothetical concept that was developed within the physics community. Nonetheless, several popular methods such as the Search of Grover, Factoring of Shor, and Linear Systems Algorithms were invented with hopes of being able to change the paradigm. The fact that the existing generation quantum computers are both robust and tiny is not stopping advancement, which is accelerating at an incredible pace, in part, due to the assistance given by the general population and the business world. The National Quantum Initiative Act has just been passed. This step provided up to 1.2 billion dollars research grants to accelerate the creation of the quantum field. There has been an increase in the level of funds spent by the private sector on funding different forms of research and as start up capital. Quantum machine learning is a new sub-discipline that brings ideas and methods of quantum computing and machine learning together. It seeks to make use of the quantum characteristics of quantum systems to address problems whose solutions cannot be obtained using classical machine learning algorithms. Quantum computing is a sub-field of computer science that addresses quantum-mechanical systems, including superposition and entanglement, to compute tasks. Quantum algorithms have the potential to provide exponential improvements over classical algorithms on particular problems, and thus are well-adapted to particular machine learning tasks. Machine learning on the other hand is part of artificial intelligence that concerns itself with development of algorithms capable of learning by data and then making predictions. There are various applications of machine learning such as computer vision, natural language processing and random access. Quantum machine learning seeks to unite the capabilities of quantum computing and machine learning to solve problems beyond the capability of either. The area is still under development, but already demonstrates good results in quantum principal component analysis, quantum support vector machines and quantum neural networks.

Related Work

Theoretical fundamentals of quantum computing were formulated by Richard Feynman in his article [1] during which he described a computer that could be able to simulate quantum physics after which how a quantum computer could be realized was explained by Ignacio Cirac and Peter Zoller in their article [2] where they proposed the idea that a quantum computer could be implemented by trapping cold ions and interacting them with laser beams. Since then, much of the hardware and advancements have been achieved in quantum hardware and in the future years a quantum computer of approximately 1000 qubits is projected. Parallel to the development of quantum hardware, quantum algorithms have been developed at a very rapid pace. The power of quantum algorithm has already been demonstrated by Shor algorithm by Algorithm [3] and Grover algorithm by search in the unstructured databases, respectively. During the early years, fewer quantum algorithms to search and factorization were written although nowadays, different classes of quantum algorithms include algebraic, optimization, approximation, search and machine learning that are rapidly being written. Quantum algorithms that facilitate machine learning have contributed to the development of the new field known as the Quantum Machine Learning (QML).

The first reference to the quantum inspired computing paradigm was [5] by Moore and Narayan in 1995 in which they talked about quantum inspired versions of selection sort and 15 puzzle problem. Ever since, numerous optimization algorithms (quantum particle swarm optimization, quantum ant colony optimization, quantum fish swarm optimization etc.) based on quantum computing have been invented and applied to different areas [6], [7], [8]. In particular, quantum genetic algorithms, as well as quantum evolutionary algorithms have been more efficiently applied using quantum advantage in [9], [10], [11], [12]. The [13] proposed Quantum inspired Neural Networks (NNs) in terms of Quantum computing and multi-agent system and offered shorter training time as a result of the capability of powerful parallel processing. The recent contributions to quantum inspired NNs involve the application of quantum inspired differential algorithm to deep belief networks that enhance global search capability and overcome the premature convergence [14], the design of a quantum inspired complex valued neural network of multimodal sentiment analysis that utilizes superposition and entanglement to interact modalities and produce similar results as those of current classical sentimental analysis methods [15]. Despite these numerous advantages of this quantum inspired method of machine learning, inconsistency of measurement is a problem at times. This challenge might be managed effectively in future and more quantum inspired versions of algorithms might arise exploiting the parallel processing power of quantum algorithms.

Universal Quantum Computing

Universal quantum computing The concept of universal quantum computing is that any quantum computation that can be mathematically modeled can be executed on a quantum computer despite the particular quantum system it uses as a Universal quantum calculator. This enables quantum computers to solve some kind of problems in a much faster manner than the classical computers. Nevertheless, universal quantum computing remains in its early stages and is regarded as a highly difficult field of research as qubits are delicate and finicky and their states are hard to measure and control. Nonetheless, numerous businesses and research centers are currently working on the development of practicable universal quantum computers and how they are applicable regardless of these difficulties.

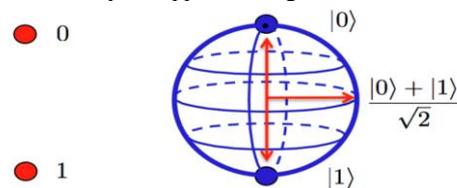


Figure 1 : Qubit

Superposition and entanglement

The principles of quantum mechanics, quantum computing base on quantum superposition and entanglement. According to superposition, similarly to waves in classical physics, any two (or more) quantum states can be superposed or added together, and the result will be a valid quantum state. Consequently, any quantum state may be defined as a superposition of two or more other quantum states. The solutions to Schrodinger equation have a property called superposition. Also, because the Schrodinger equation is a linear equation, any linear combination of solutions will be a solution.

The qubit state in quantum computing is a quantum superposition of $|0\rangle$ and $|1\rangle$. This implies that the likelihood of measuring a qubit as 0 or 1 is not 0.0 or 1.0 and consecutive measurements of qubits in the same states will not produce consistent measurements.

The other element in quantum computing is quantum entanglement. The measurement or measurement of the state of qubits is problematic. Quantifying a qubit in superposition to ascertain its value will make it acquire a value of either 1 or 0, but not a resultant mixture of the two. That effectively nullifies the working of the quantum computer. It requires the use of indirect measurements to preserve the integrity of a quantum computer. An answer is given through entanglement.

classical and quantum computing

The integration of classical and quantum computing is a process that entails the use of the respective computing strengths to address problems. Processing, management and storage of data, as well as working with volumes of classical data, are all tasks that classical computing is best suited to undertake. Alternatively speaking, quantum computing is most effectively used in solving some kinds of problems which are hard or impossible to solve with classical computing, like the simulation of quantum systems, optimization problems, and breaking some encryption algorithms.

With the integration of the two kinds of computing, one can be able to capitalize on the advantages of the two to tackle intricate issues. As an example, one can take large volumes of classical data and pre-process it using a classical computer and then send it to a quantum computer to do the more complicated computations. The quantum computations can then be handled and analyzed by the classical computer. Another category of algorithm is the hybrid algorithm which uses both the classical and quantum computing to solve problems which can be reduced into smaller problems where some of them can be solved by using classical computing and some cannot be solved without quantum computing.

The science of integrating classical and quantum computing is still young, and there are numerous tasks to be met such as the creation of efficient algorithms, the connection of the classical and quantum hardware, and the scaling of quantum computers to larger scales. Nonetheless, this combination has the potential to bring significant benefits and, therefore, it is a promising research and development field.

Quantum Machine Learning Applications

Quantum machine learning is another branch of machine learning that leverages the power of quantum computer and machine learning algorithms to tackle difficult problems. Quantum machine learning has a number of possible applications, which include:

Image and video analysis: Image and video analysis can be applied to quantum machine learning through quantum machine learning algorithms to analyze objects and track objects, which are better than classical algorithms.

Natural language processing Natural language processing (NLP) tasks like sentiment analysis and language translation can be enhanced with quantum machine learning algorithms to take advantage of quantum system parallelism and representational ability.

Recommender systems: Quantum machine learning algorithms can be applied to making recommender systems, including systems used to make personalized shopping recommendations, to consider more variables and more complex relationships among them.

Anomaly detection: The quantum machine learning algorithms may be applied to carry out anomaly detection in large datasets, including fraud in financial transactions, or faulty manufacturing processes.

Optimization problems: Applications of quantum machine learning include optimization problems, i.e. minimizing the value of a complex function, by taking advantage of the capability of quantum systems to explore broad solution space simultaneously.

The above are only some of the possible applications of quantum machine learning. Although the field is still in its infancy, it promises a lot to enhance the validity and efficiency of machine learning algorithms and resolving complex problems in most areas.

Quantum subroutines

Quantum subroutines are small quantum algorithms that can be combined and used as building blocks to solve larger problems. They are similar in concept to subroutines in classical computing, where complex algorithms are broken down into smaller, reusable units that can be combined to solve larger problems.

Quantum Fourier Transform

The Quantum Fourier Transform (QFT) is a quantum algorithm that is used to perform a type of transformation called the Fourier transform. The Fourier transform is a mathematical operation that transforms a signal from the time domain to the frequency domain, which can be used to extract information about the frequencies present in the signal.

The QFT is a quantum version of the classical Fourier transform, and it has the advantage of being able to perform the transformation much faster than classical algorithms, especially for large data sets. This makes the QFT a key component in many quantum algorithms, including those used for quantum cryptography, quantum simulation, and quantum optimization.

The Quantum Fourier Transform (QFT) is defined mathematically as follows:

Given an n -qubit state vector $|x\rangle$, the QFT transforms it into a state vector $|y\rangle$, where:

$$|y\rangle = \frac{1}{\sqrt{2^n}} \sum_{j=0}^{2^n-1} e^{i2\pi j/2^n} |j\rangle$$

where $|j\rangle$ is the computational basis state and e is the mathematical constant approximately equal to 2.71828.

In other words, the QFT is a linear transformation that maps the computational basis states $|j\rangle$ to the frequency states $|y\rangle$. The coefficients in the transformation are given by the exponential terms, which encode the relative phase of each frequency component.

The QFT can be implemented using quantum gates and circuits, such as the Hadamard gate, the phase shift gate, and the controlled rotation gate. The specific implementation of the QFT depends on the number of qubits and the desired accuracy, and there are several different algorithms for performing the QFT that have been developed over the years.

Quantum Phase Estimation Algorithm

The Quantum Phase Estimation Algorithm (QPE) is a quantum algorithm used to estimate the eigenvalues of a unitary matrix. The algorithm is defined mathematically as follows:

Given a unitary matrix U and its eigenvector $|\psi\rangle$ with eigenvalue $e^{i2\pi\theta}$, where θ is the unknown eigenphase, the QPE algorithm estimates θ using the following steps:

Initialize a quantum state $|0\rangle$ and apply the controlled- U operation, where $|0\rangle$ is used as the control qubit and U is the target unitary matrix:

$$|\psi\rangle = (|0\rangle \otimes |0\rangle) \rightarrow CU|\psi\rangle = (|0\rangle \otimes U^0|0\rangle)$$

Apply the inverse quantum Fourier transform (IQFT) to the second register:

$$|\psi\rangle = (|0\rangle \otimes \frac{1}{\sqrt{2^n}} \sum_{j=0}^{2^n-1} e^{i(2\pi j/2^n)} U^j |0\rangle)$$

Measure the second register to obtain an estimate of θ . The result of the measurement will be a binary number m , which can be used to estimate θ as follows:

$$\theta_{\text{estimate}} = m/2^n$$

The QPE algorithm can be repeated multiple times to obtain a more accurate estimate of θ , and the accuracy of the algorithm can be improved by increasing the number of qubits in the second register. Overall, the QPE algorithm is a useful tool for estimating the eigenvalues of a unitary matrix, and it has many potential applications in fields such as quantum simulation, quantum optimization, and quantum cryptography.

Quantum Annealing

Quantum annealing is a constrained form of computation mechanism, although it has been advancing, in the type of Moore law progress, in the last two years. This kind of system has at least some form of use. The concept is to project issues into this functionality and then apply the quantum processor in order to address the relevant issue. The system can be imagined as a hills and valleys landscape to see this. The minimum point is linked with the solution. The same way that water will be found in the lowest valleys, the solution will also be annotated by the annealer. The D Wave 2x system has also been demonstrated to be able to solve optimization problems that are up to 108 times faster than simulated annealing as well as quantum monte carlo. The usefulness of the system is now demonstrated by more recent works.

Quantum Machine Learning(QML)

When the general hardware is introduced, it is valuable to step out and have a look at how these systems can be utilized in the machine learning sense. Since quantum computing is fundamentally not the same as classic type of computing, so can quantum machine learning be applied in radically different ways. As an illustration, since quantum annealers are naturally the minimizers of the energy states, optimization problems can be represented in such systems. The quantum HHL algorithm - a quantum system solving equation technique that takes advantage of the fundamental quantum effect can be used in numerous machine learning applications. The search algorithm of Grover exploits the quantum effect of amplitude amplification in marking solutions of an unsorted database. This can have one implication that is, clustering potentially can occur in a much faster way. In summary, quantum computing offers developers of machine learning methods with tools that were not available before. This enables the possible quicker processing of the information and the creation of new types of algorithms. In this regard, it is worth noting that one should not only know the existing systems available but also recent developments.

QML Algorithms

Here is a list of some of the most commonly used quantum machine learning (QML) algorithms:

- Quantum Principal Component Analysis (PCA)
- Quantum Support Vector Machines (SVM)
- Quantum K-Means Clustering
- Quantum Linear Regression
- Quantum Neural Networks
- Quantum Decision Trees
- Quantum Random Forest
- Quantum Naive Bayes Classifier
- Quantum Convolutional Neural Networks
- Quantum Autoencoders

These algorithms are based on classical machine learning algorithms and they use quantum circuits and quantum gates to process and analyze data in a quantum computing environment. They offer potential advantages over classical machine learning algorithms, such as exponential speedup for certain types of problems, better handling of high-dimensional data, and improved robustness against adversarial attacks.

Quantum Support Vector Machines (QSVM)

QSVM is a quantum machine learning (QML) algorithm that performs binary classification on data, similar to classical Support Vector Machines (SVM). It is a type of supervised learning algorithm that is used to classify data into two categories based on their features.

Quantum Support Vector Machines (SVM) is a quantum machine learning (QML) algorithm that performs binary classification on data, similar to classical Support Vector Machines (SVM). It is a type of supervised learning algorithm that is used to classify data into two categories. In a classical SVM, the optimization problem that finds the hyperplane is solved using numerical methods. In a quantum SVM, the optimization problem is solved using quantum algorithms, such as Grover's search algorithm or amplitude amplification. The goal is to speed up the optimization process and find the solution faster than classical SVM algorithms.

Quantum SVM algorithms have shown promise in simulation, but there is still much work to be done before they can be applied to real-world problems. The field of quantum machine learning is still in its early stages, and there are many challenges to be addressed, such as the development of quantum algorithms that can handle large datasets, quantum error correction, and the development of quantum hardware that can run these algorithms in a scalable manner.

Table 1. Comparison among the QSVM algorithms

Algorithm	Approach	State Preparation scheme	Kernel function	Speed-up	Complexity	Performance
Improved QSVM	simulation and matrix-inversion based	QRAM	Nonlinear	Exponential	Poly-logarithmic	Accuracy 0.9514
QSVM	HHL algorithm based	Linear mapping	Linear	Exponential	-	Accuracy 99.5% (OCR) 98% (Iris)
HVQ-SVM	Hybrid variables based	QPCA and QSVT	Nonlinear	Exponential	Poly- logarithmic	N.I.

Quantum K-Means Clustering

In quantum K-Means, quantum algorithms are used to perform the optimization, allowing for potentially faster convergence and improved accuracy. The use of quantum computers also opens up the possibility of using quantum-inspired techniques, such as quantum annealing, to solve the K-Means optimization problem. While quantum K-Means is still an area of active research, there have been some promising results, with quantum algorithms showing the potential to outperform classical algorithms in terms of speed and accuracy. However, it's important to note that quantum computing is still in its early stages and more research is needed to fully realize the potential of quantum K-Means and other quantum machine learning algorithms.

Quantum Neural Networks

Quantum Neural Networks (QNNs) are a type of neural network that uses quantum mechanics to perform computations. They are based on the same principles as classical neural networks, but use quantum bits (qubits) instead of classical bits to store and process information.

QNNs have several advantages over classical neural networks:

Parallelism: In a quantum computer, many computations can be performed simultaneously, which allows for much faster processing of information.

Expressiveness: QNNs have the ability to perform complex computations using a limited number of qubits, which makes them well-suited for solving problems in areas such as cryptography and quantum simulation.

Robustness: Quantum mechanics allows for robust computation, which makes QNNs more resilient to errors and noise.

Table 2. Summarized Comparison among the different QNNs

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

Quantum Machine Learning Tools

TensorFlow Quantum: This is a library developed by Google for implementing quantum algorithms using TensorFlow. It provides a high-level API for developing quantum circuits and running quantum computations on quantum hardware or simulators.

Cirq: This is an open-source library for creating, editing, and invoking quantum circuits. It is designed for use with quantum hardware and simulators, and can be integrated with other machine learning libraries such as TensorFlow.

PennyLane: This is a library for quantum machine learning that provides a unified interface for quantum hardware and software simulators. It includes features such as automatic differentiation and device-agnostic quantum functions.

QuTIP: This is a quantum toolbox in Python that provides a variety of tools for quantum mechanics and quantum computing, including functions for quantum machine learning and quantum control.

Qiskit: This is an open-source framework for quantum computing that provides tools for quantum algorithm development, quantum circuit design, and quantum hardware integration.

Strawberry Fields: This is a full-stack library for quantum photonics, including a set of tools for quantum machine learning. It provides features such as variational quantum algorithms and quantum neural networks.

These are just a few examples of the tools and libraries available for developing QML algorithms and applications. The field of QML is still in its early stages of development, and new tools and libraries are being developed all the time.

Quantum Machine Learning applications in real world

Quantum Machine Learning (QML) is an interdisciplinary field that combines quantum physics and machine learning. It aims to leverage the unique properties of quantum systems, such as superposition and entanglement, to solve problems in machine learning and artificial intelligence. Currently, QML is still in the early stages of development and there are few real-world applications of it. However, some potential use cases for QML include:

Optimization problems: Quantum computers can perform certain types of optimization problems much faster than classical computers, which makes them ideal for solving complex optimization problems in machine learning.

Quantum feature extraction: QML can be used to extract features from quantum data that can be used to train machine learning models.

Quantum neural networks: Quantum neural networks have the potential to perform better than classical neural networks for certain types of problems, such as quantum control and quantum simulation.

Quantum unsupervised learning: Unsupervised learning algorithms can be applied to quantum systems to discover new quantum states and quantum phases.

Quantum natural language processing: QML has the potential to significantly improve the performance of natural language processing algorithms, especially for tasks such as sentiment analysis and text classification.

While these applications are still largely theoretical, there is significant interest and research in the field of QML, and it is expected to play an important role in the future of machine learning and artificial intelligence.

Conclusion

A revolutionary benefit in the field of machine learning is promised by quantum machine learning. The enormous quantity of data being produced and technical advancements in recent years may make it challenging for the probabilistic and optimization-based classical machine learning algorithms to offer solutions to issues in the real world. Future ML issues are better served by QML based on entanglement and superposition in quantum computing. On present hardware, QML implementation is still not feasible for computationally intensive applications employing massive datasets. This might not be a problem in the future because to developments in fault-tolerant quantum systems and quantum technology. The path to effective quantum machine learning has already been established, and the implementations of QSVMs, Quantum classifiers, and QNNs covered in this work provide a preview of how future QML algorithms can assist in resolving optimization and decision-making issues.

References

1. Feynman, Richard P. (1982) "Simulating physics with computers." *International Journal of Theoretical Physics* 21(6) : 467–488.
2. Cirac, Juan I., and Peter Zoller (1995) "Quantum computations with cold trapped ions" *Phys. Rev. Lett.* 74 : 4091–4094.
3. Shor, Peter W. (1999) "Polynomial-time algorithms for prime factorization and discrete logarithms on a quantum computer" *SIAM Review* 41 : 303–332.
4. Grover, Lov K. (1997) "Quantum computers can search arbitrarily large databases by a single query" *Physical review letters* 79(23) : 4709.
6. Moore, Mark, and Ajit Narayanan. (1995) "Quantum-inspired computing" *Dept. Computer. Sci., Univ. Exeter, Exeter, UK* : 1-15.
7. Wan, Lanjun, Hongyang Li, Yiwei Chen, and Changyun Li. (2020) "Rolling bearing fault prediction method based on qpso-bp neural network and Dempster–Shafer evidence theory" *Energies* 13 (5) : 1094.
8. Kumar, Nirmal, Sanat Kumar Mahato, and Asoke Kumar Bhunia. (2020) "A new qpso based hybrid algorithm for constrained optimization problems via tournamenting process" *Soft Computing* 24 (15) : 11365–11379.
9. Li, Junjun, BOWEI XU, Yongsheng Yang, and Huafeng Wu. (2020) "Quantum ant colony optimization algorithm for agvs path planning based on bloch coordinates of pheromones" *Natural Computing* 19(4) : 673–682.
10. SaiToh, Akira, Robabeh Rahimi, and Mikio Nakahara. (2014) "A quantum genetic algorithm with quantum crossover and mutation operations" *Quantum Information Processing*.13(3) :737–755.
11. Wang, Xinpeng, Shengxiang Huang, Guanqing Li, Wen Zhang, Chenfeng Li, and Yarong Wang. (2020) "Adaptive stochastic resonance method based on quantum genetic algorithm and its application in dynamic characteristic identification of bridge gns monitoring data" *IEEE Access* 8 : 113994–114009.
12. Zheng, Suqing, Jun Xiong, Lei Wang, Dong Zhai, Yong Xu, and Fu Lin. (2021) "e-graphene: A computational platform for the prediction of graphene-based drug delivery system by quantum genetic algorithm and cascade protocol" *Frontiers in chemistry* 9 : 1-15.
13. Guofeng, Zhang, and Askar Hamdulla. (2021) "Adaptive morphological contrast enhancement based on quantum genetic algorithm for point target detection" *Mobile Networks and Applications* 26(2) : 638–648.
14. Meng, Xiangping, Jianzhong Wang, Yuzhen Pi, and Quande Yuan. (2007) "A novel ann model based on quantum computational mas theory" *International Conference on Life System Modeling and Simulation*. Springer : 28–35.
16. Deng, Wu, Hailong Liu, Junjie Xu, Huimin Zhao, and Yingjie Song. (2020) "An improved quantum-inspired differential evolution algorithm for deep belief network" *IEEE Transactions on Instrumentation and Measurement* 69(10) : 7319–7327.
17. Li, Qiuchi, Dimitris Gkoumas, Christina Lioma, and Massimo Melucci. (2021) "Quantum-inspired multimodal fusion for video sentiment analysis" *Information Fusion*. 65 : 58–71.
18. Chen, Junwen, Xuemei Qi, Linfeng Chen, Fulong Chen, and Guihua Cheng. (2020) "Quantum-inspired ant lion optimized hybrid k-means for cluster analysis and intrusion detection", *Knowledge-Based Systems* 203 : 106167.
19. Altaisky, Mikhail V., Natalia E. Kaputkina, and V. A. Krylov. (2014) "Quantum neural networks: Current status and prospects for development", *Physics of Particles and Nuclei* 45(6) : 1013-1032.
20. Tacchino, Francesco, Chiara Macchiavello, Dario Gerace, and Daniele Bajoni. (2019) "An artificial neuron implemented on an actual quantum processor" *npj Quantum Information* 5(1) 1–8.
21. Niu, Xu-Feng, and Wen-Ping Ma. (2021) "A novel quantum neural network based on multi-level activation function" *Laser Physics Letters* 18(2) : 025201.
23. Yang, Chao-Han Huck, Jun Qi, Samuel Yen-Chi Chen, Pin-Yu Chen, Sabato Marco Siniscalchi, Xiaoli Ma, and Chin-Hui Lee. (2021) "Decentralizing feature extraction with quantum convolutional neural network for auto-matic speech recognition" in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* : 6523– 6527.
24. Trugenberger, Carlo A. (2002) "Quantum pattern recognition" *Quantum Information Processing* 1(6) :471–493.
25. Schuld, Maria, Ilya Sinayskiy, and Francesco Petruccione. (2014) "Quantum computing for pattern classification" in *Pacific Rim International Conference on Artificial Intelligence*, Springer : 208–220.
26. Lu, Songfeng, and Samuel L. Braunstein. (2014) "Quantum decision tree classifier" *Quantum information processing* 13(3) : 757–770
27. Zhou, RiGui, WenWen Hu, GaoFeng Luo, XingAo Liu, and Ping Fan. (2018) "Quantum realization of the nearest neighbor value interpolation method for INEQR" *Quantum Information Processing* 17(7) : 1–37.
28. Nawaz, Syed Junaid, Shree Krishna Sharma, Shurjeel Wyne, Mohammad N. Patwary, and Md Asaduzzaman. (2019) "Quantum machine learning for 6G communication networks: State-of-the-art and vision for the future" *IEEE Access* 7 : 46317–46350