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A Comprehensive Survey on Quantum Machine Learning and Possible Applications

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ABSTRACT

Machine learning is a branch of artificial intelligence that is being used at a large scale to solve science, engineering, and medical tasks. Quantum computing is an emerging technology that has a very high computational ability to solve complex problems. Classical machine learning with traditional systems has some limitations for problem-solving due to a large amount of data availability. Quantum machine learning has high performance and computational ability that can effectively be used to solve computation tasks. This study reviews the latest articles in quantum computing and quantum machine learning. Building blocks of quantum computing and different flavors of quantum algorithms are also discussed. The latest work in quantum neural networks is also presented. In the end, different possible applications of quantum computing are also discussed.

KEYWORDS

Hybrid Computing, Machine Learning, Neural Networks, QML, Quantum, Quantum Algorithms, Quantum Computing, Quantum-Inspired

1. INTRODUCTION

Due to the improvement of computational ability ML has become a very important field to automatically analyze different tasks. A machine learning algorithm can analyze a large amount of data in terms of making an intelligent decision based on training data. The learning process in machine learning is mainly divided into three categories unsupervised, supervised, and re-enforcement learning. The first two categories are mainly utilized for data mining and data analysis tasks while re-enforcement learning is for interactive tasks where learning increased at every step. In the last two decades, with advancements in technology, computing power has increased rapidly, and new algorithms have come up continuously. Different studies have been proposed in which different classical ML and deep learning techniques are utilized in the literature (Akbar et al., 2017; Akhtar et al., 2020; Akram et al., 2018; Amin et al., 2016a, 2016b; Amin, Sharif, Rehman, et al., 2018; Amin, Sharif, Yasmin, Saba, Anjum, & Fernandes, 2019b; Sharif et al., 2017; Sharif, Khan, et al., 2018; Sharif et al., 2019, 2020; Sharif & Shah, 2019). Machine learning is being applied at a large scale in

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medical diagnosis for example brain tumor detection with classical methods are presented in (Amin, Sharif, Gul, Raza, Anjum, Nisar, et al., 2019; Amin, Sharif, Raza, et al., 2018; Amin, Sharif, Raza, Saba, & Anjum, 2019; Amin, Sharif, Raza, Saba, & Rehman, 2019; Amin, Sharif, Yasmin, et al., 2018; Amin, Sharif, Yasmin, Saba, Anjum, & Fernandes, 2019a, 2019b; Khan et al., 2019; Masood et al., 2013; Raza et al., 2012; Saba et al., 2020; Sharif, Tanvir, et al., 2018; Yasmin, Mohsin, et al., 2012; Yasmin, Sharif, et al., 2012a, 2012b). Breast cancer detection by using the classical ML and deep learning are presented in (Mughal et al., 2017, 2018, 2019; Mughal & Sharif, 2017; Yasmin et al., 2013). Different studies in which classical computing is utilized for solution of different tasks are presented in (Amin, Sharif, Yasmin, Ali, et al., 2017; Amin, Sharif, Yasmin, & Fernandes, 2017; Arunkumar et al., 2017; S. L. Fernandes et al., 2017; Raja et al., 2018; Rajinikanth et al., 2017). The data growth is also increasing at a much higher rate as compared to the computer's performance. So, in the area of classical ML computing power is reducing due to the high complexity of big data.

Quantum computing is an emerging technology that offers a more efficient way to deal with complex and high computational tasks as compared to classical computations because it has a fundamentally different solution to computational problems. The quantum computer's problem-solving mechanism is purely based on a fundamental concept of quantum mechanics more precisely consist of quantum interference, quantum superposition, and entanglement (Imre, 2013; Imre & Gyongyosi, 2012; Nielsen & Chuang, 2002). Quantum computing is an emerging technology that may be available commercially in the coming few years because it has promising results on computational problems (Barends et al., 2014; Biamonte et al., 2017; Debnath et al., 2016; DiCarlo et al., 2009; Higgins et al., 2007; Ofek et al., 2016). In quantum computing to solve a specific problem, a high degree of parallelism can be achieved in a specific algorithm due to the paramount feature of high-speed computing. Shor's prime factorization solution is the one of example of demonstration of quantum computing power in terms of exponential speedup, which shows that factorization problem of big integer can be solved with quantum computing that is impossible to solve with classical method (Shor, 1997). After that a large number of studies are presented to solve the special problems for example, to searching in unstructured database Grover's algorithm showed that a quadric speed can be achieved with quantum computing (Grover, 1997). Rivest -Shamir-adleman (RSA) algorithm is an example to differentiate between the capacity of problem solving in terms of speedup by using traditional and quantum computing (Rivest et al., 1978). Solving some complex computational problems by using classical computing may require billions of years while in theory these complex computational problems may be solved in few hours with the help of quantum computing (Proos & Zalka, 2004).

Quantum computing has strong computation ability as compared to traditional computing so, the combination of QC and ML is the hot research area and a large amount of research work is being carried out to apply machine learning on quantum computers, this phenomenon is called QML. Recently, the progress of developing quantum computers is being increased for instance D-wave special-purpose quantum computers can run some traditional machine learning algorithms on it with high efficiency and can also perform quantum annealing (F. Hu et al., 2019). Large-scale quantum computing devices are being developed to run a quantum version of classical machine learning algorithms on it. Some advanced companies and research centers are trying to produce actual quantum circuits based on universal quantum computers that can effectively be used to perform quantum computational experiments on a lower amount of qubits with the help of cloud computing platforms. Nowadays, Quantum machine learning-based algorithms are also showing increased progress. Different classical ML algorithms, for example K-mean clustering, SVM, and dimensionality reduction algorithms have got their quantum version to run on quantum computers for performance enhancement. Quantum counterparts of some aforementioned classical ML algorithms have also been tested on real quantum computers (W. Hu, 2018; Z. Li et al., 2015; Tao Xin(辛涛) & Tao Xin(辛涛), 2018; Xin et al., 2020). Quantum versions of different machine learning algorithms are largely discussed in the literature, recent survey papers on quantum machine learning are presented in (Adcock et al., 2015; Oshurko, 2016; Schuld et al., 2015; Schuld & Killoran, 2019).

Due to high processing speed, quantum computing is being utilized to solve heavy computational tasks that are harder to solve with classical computing. Quantum computing is successfully utilized in Financial modeling tasks because of the stochastic nature of financial markets that can be model with help of inherited randomness of quantum computing (Egger et al., 2020; Orus et al., 2019; Palsson et al., 2017). Today stock exchange that has a worth of million-dollar is being controlled with classical computers, this type of complex problem can efficiently be solved with the power of quantum ML. Weather forecasting is another example of complex computing that has been a long goal for scientists can also be better modeled with the help of quantum computers due to the large parallel computing power of these systems. Classical computers have limited computing power and different difficulties may arise to model the complex molecules. Chemical reactions have a quantum nature and highly entangled quantum superposition states are involved in their formation (J. Li & Kais, 2019). Quantum computers can effectively be used to accurately model these states. Quantum cryptography is another interesting area of quantum computing that is the utilization of quantum mechanical attributes to accomplish the cryptographic stint. BB84 protocol for secure quantum key distribution is the foundation of quantum cryptography was presented by Bennett et al. as this type of security was impossible to achieve with classical computers (Bennett et al., 1992; Pathak, 2013).

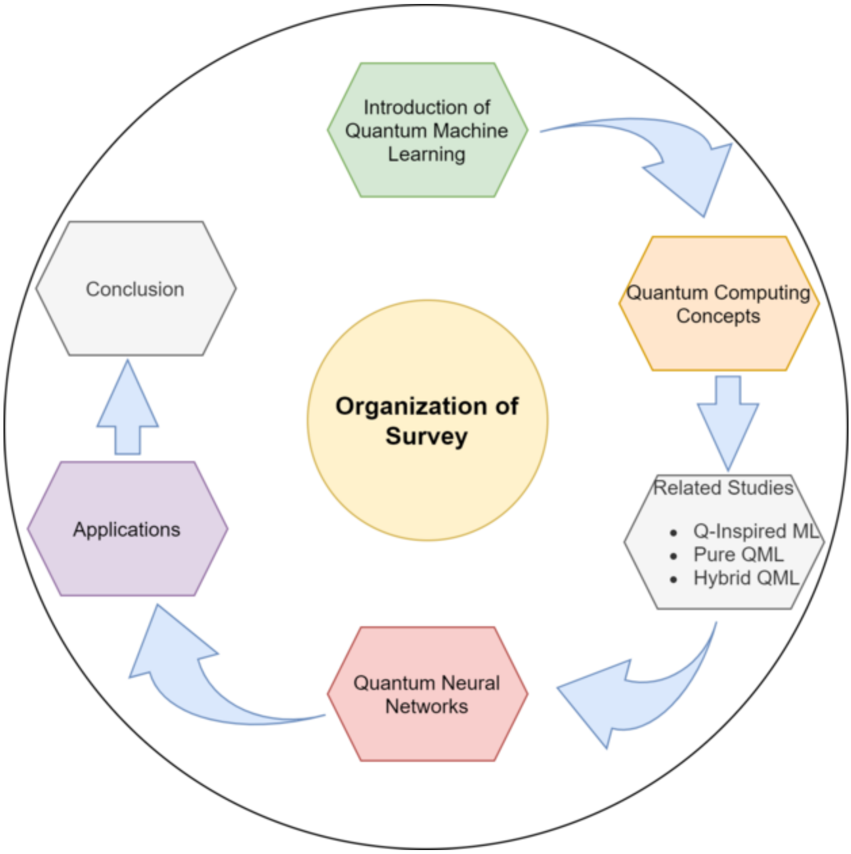
All classical computing systems, for example, smartphones, laptops, and servers rely on a fundamental concept of storing and manipulating information in the form of individual bits having two states zero and one. To process and display information in classical computers millions of bits work together to solve or run any task. While in quantum computers a physical phenomenon of quantum mechanics is utilized to manipulate information. In quantum computers for information processing quantum bits or qubits are utilized. Contrasted to a bit where values are zero or one or a combination of these, in qubits, a concept of superposition is utilized in which complex-value-weighted states may purposefully be entangled into linear combinations across the qubits. The purpose of quantum computers is to solve the extremely large and complex computing task that is time-consuming and needs a lot of parallel processing power so, these are not the replacement of classical ones and thus are a complement to solve high computational tasks. Recently, remarkable progress is seen in the hardware construction of quantum computers that led to the development of quantum systems with ten qubits and dubbed as noisy quantum processors in absence of quantum error correlation (Preskill, 2018). Quantum computers have the potential to solve complex and high computational tasks faster than classical systems, the advantage of quantum to classical systems is presented in (Bravyi et al., 2018). Fault-tolerant universal quantum computers are also in the way to develop that require error correction (Aharonov & Ben-Or, 2008; Campbell et al., 2017; Gottesman, 1997).

This article reviews the latest studies in quantum computing and also discusses the different flavors of quantum algorithms. Building blocks of quantum computing and quantum neural networks with possible applications of QML in different areas are also discussed. The graphical general workflow of the proposed study is given in figure 1.

2. QUANTUM COMPUTING CONCEPTS

Quantum computing has become the most important new growth research field due to the high computational ability to solve complex tasks. Quantum machine learning is showing significant progress and success in different fields including medical image analysis and different classification tasks. In the medical and networks area classical machine learning is applied at a large scale to automate the manual diagnosis of different diseases (D. Chakraborty et al., 2021; S. Fernandes et al., 2019; S. L. Fernandes et al., 2020; S. L. Fernandes & Bala, 2016; S. L. Fernandes & Jha, 2020; ORTIZ et al., 2021; Wang et al., 2021). Quantum machine learning-based diagnosis systems are also gaining increased intention (Umer et al., n.d.). Building blocks of quantum computing for QML are presented in detail below.

Figure 1. General workflow of the survey



In classical computing devices for information processing and storing bits are utilized as a basic unit while in quantum computing basic unit for information processing is known as a quantum bit or qubit. A basic notation of representing qubits is given in equation 1:

$$\left|1\right. = \begin{pmatrix}0\\1\end{pmatrix}, \left|0\right. = \begin{pmatrix}1\\0\end{pmatrix} \tag{1}$$

These bits can be at both states simultaneously according to superposition that is not possible in classical systems as presented in equation 2:

$$\left|\delta\right. = A\left|0\right. + B\left|1\right. = \begin{pmatrix}A\\B\end{pmatrix} \tag{2}$$

Here A, B ϵ C and $\left|A\right|^2 + \left|B\right|^2 = 1$ which show the $|\ \delta$ is in both state zero and one at the same time. On measuring the probability of state zero and one will be $\left|A\right|^2$ and $\left|B\right|^2$ respectively (Bennett & DiVincenzo, 2000; Nielsen & Chuang, 2010; Y. Zhang & Ni, 2020).

Basic quantum circuits that are operating on qubits are known as quantum gates. Quantum gates are the main building block in quantum computation systems same as logic gates that are used in the classical system for designing digital circuits (Y. Zhang & Ni, 2020). The specialty of quantum gates is that these are all reversible gates as this property is not available in classical logic gates so, for representation of quantum gates unary matrices are utilized which means that the number of inputs and outputs are always the same in quantum gate circuits. Quantum gates in reality are operators that are used to transform one quantum state into another quantum state with unitary matrices are represented in equation 3:

$$U\left|\delta = \begin{pmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{pmatrix}\begin{pmatrix} A \\ B \end{pmatrix} = \begin{pmatrix} a \\ b \end{pmatrix} = \right|\varnothing \tag{3}$$

Measurement is the core problem of quantum mechanics interpretation in quantum computing that currently has no consensus. Here we are only considering the practical physics measurements without worrying about the philosophical differences (Y. Zhang & Ni, 2020). A collection of measurement W_w operators is used to describe the quantum measurements as reported by the quantum postulate. The system measurements are taken from the state space that is under these operators. Experimental outcomes in the form of measurements are represented by the index w. To calculate the probability of result (w), if the quantum state system ($|\delta$) is given following equation 4 can be used:

$$\Pr\left(w\right) = \left|\delta \, W^{+}{}_{w} W_{w} \delta \right| \tag{4}$$

The system state after the measurement is presented in equation 5:

$$\frac{W_{w}\delta \mid}{\sqrt{\left|\delta \, W^{+}{}_{w} W_{w} \delta \right|}} \tag{5}$$

3. RELATED STUDIES

To understand the importance and applications of QC a detailed review of QC and QML is presented in this section. For an insight of basic concept of quantum computing interested readers are referred to read these books (Imre & Gyongyosi, 2012; Nielsen & Chuang, 2002) while for the understanding of quantum communication network see also (Meter, 2014). Problems related to quantum computation are discussed in (Penrose, 1999). Bennett et al. presented a study to discuss the strength and weaknesses of quantum computing (Bennett et al., 1997). The latest progress on quantum algorithms is presented in (Bacon & van Dam, 2010). To study the prime factorization problem solution with the help of quantum computing one can read Shors's article on it (Shor, 2006). An essential study on universal quantum computers is presented in (Deutsch & Penrose, 1985). Simulation of quantum computing with classical computers with complete detail is presented in Feynman's article (Feynman, 1982). A study on quantum computing coherence with its attributes and method to maintain it is presented by Unruh (Unruh, 1995). Basic quantum complexity theory with detail is proposed in (Bernstein & Vazirani, 1997). The explanation to solve the algebraic problem with the help of advanced quantum computing is discussed in (Childs & van Dam, 2010). To study the quantum computing speedup phenomena in detail interested may study a detailed article on it (Jozsa & Linden, 2003). Basic building blocks and implementation detail of spin quantum systems in term matrix product states can be found in (Verstraete et al., 2008). To find out the temporary issues related to unstructured quantum computation one can read (Shepherd & Bremner, 2009). To study the main problem related to multiparty quantum computing delegation systems interested readers may access it (Kashefi & Pappa, 2017). A survey on difficult quantum simulation problems is presented in (Georgescu et al., 2014).

This review mainly categorized quantum machine learning into three approaches such that quantum-inspired machine learning, hybrid classical-quantum machine learning, and pure QML. These three approaches are mainly categorized into three classes based on the variety of data and algorithms that are used to solve a specific task for example which kind of algorithm is being used (quantum or classical) and what kind of data to use (quantum or classical data) (Aïmeur et al., 2006; Dunjko et al., 2016). Applications with an overview of different kinds of quantum algorithms with detail are presented by Montanaro (Montanaro, 2016). A review on QNNs-based methodologies and implementations with possible applications is proposed in (Jeswal & Chakraverty, 2019). In another study, Benedetti et al. (Benedetti, Lloyd, et al., 2019) presented an overall overview of hybrid quantum computing (classical and quantum computing), in their study they also discussed the framework for the variational and encoder circuits for component modeling. Quantum machine learning challenges and progress of quantum computing technology with its applications are presented in (Ciliberto et al., 2018; Resch & Karpuzcu, 2019). Quantum computing is an emerging technology that is making progress rapidly and is being applied in machine learning and real-world problems, this article categorized quantum computing into three approaches each of which is discussed in detail in the following subsection respectively.

3.1 Quantum-Inspired Machine Learning

In this approach, to boost the traditional ML process quantum computing principle is applied. Recently, a Q-inspired binary classifier based on a theory of quantum mechanics that involves the superposition mechanism to expand the high degree of freedom for taking intelligent decisions is presented by Tiwari et al. (Tiwari & Melucci, 2018). Their proposed methodology achieved a comparable result with classical SVM and KNN classifiers. For performance evaluation accuracy and F-measures are calculated. In another study, a binary supervised learning classifier inspired by quantum computing that works based on quantum theory and density matrices is presented by Sergioli et al. (Sergioli et al., 2019). Their classifier is known as Helstrom Quantum Centroid (HQC) which was tested on fourteen different datasets and results are also compared with classical learning models. A linear transformation-based quantum-inspired novel SVM algorithm for a classification task that achieved exponential speedup is presented by Ding et al. (Ding et al., 2020). The Quantum counterpart of the decision tree classifier that depends on the quantum fidelity and entropy measures is proposed by Lu et al.(Lu & Braunstein, 2014). A novel quantum-inspired NN known as the automated perceptron model is introduced in (Sagheer et al., 2019). Comparison of the presented model with the classical algorithm shows higher accuracy and low complexity. For ridge regression analysis a new quantum learning-based methodology is presented by Yu et al.(Yu et al., 2019). Quantum SVM for clustering using quantum Gaussian and polynomial kernels is presented (Bishwas et al., 2019). A Schrodinger equation-based clustering algorithm with the quantum framework is presented in (Casaña-Eslava et al., 2019).

3.2 Hybrid Quantum Machine Learning

In this technique, to decrease the learning cost and performance enhancement the power of quantum algorithms and classical algorithms are combined. Maria Schuld et al. have solved the classification problem and presented two different hybrid quantum ML-based systems in which different kernel approaches and feature maps are used to explore the quantum world. Their study also discussed that complex computing tasks can be performed more efficiently in Hilbert's space. Results show that the quantum computing techniques performed better as compared to classical methods (Schuld & Killoran, 2019). To encode data in an N-dimensional vector a new quantum ML system that consists of a single quantum entity that utilized single shot training that needs fewer training parameters and can achieve high accuracy is presented by Soumik et al. (Adhikary et al., 2020). In another study, Havlicek et al. (Havlicek et al., 2019) proposed two versions of SVM, in the first model quantum variational circuits are used that need two algorithms for classification task one for training purposes and the other for quantum classification to correctly label the input data. In the second version of quantum SVM, a quantum kernel-based algorithm is proposed in which quantum kernel estimation is utilized. Quantum ML-based feature section method for performance enhancement in ML techniques is introduced in (S. Chakraborty et al., 2020). The Quantum KNN classification algorithm performed better as compared to its classical counterpart and is presented by Ruan et al. (Ruan et al., 2017). An unsupervised hybrid quantum-classical algorithm to characterized NISQ hardware for the solution sampling problem is proposed by Benedetti et al. (Benedetti, Garcia-Pintos, et al., 2019). Grant et.al. (Grant et al., 2018) presented a hierarchical structured-based binary classifier to solve the binary classification tasks. In another study, Zhang et al. (D.-B. Zhang et al., 2018) discussed the nonlinear regression by using hybrid quantum computing. Hybrid quantum-based solutions of different tasks such that clustering, classification, and regression are discussed in (Mitarai et al., 2018).

3.3 Pure Quantum Machine Learning

A quantum counterpart or quantum version of classical ML algorithms is known as QML that can effectively be implemented on real quantum computers. A quantum linear regression that is a counterpart of classical linear regression is presented in (Schuld et al., 2016) that works based on an N-dimensional quantum feature vector with logarithmic time. Willsch et al. (Willsch et al., 2020) presented a quantum version of SVM by implementing it on a quant annealer device (Headquarters, 2020) abbreviated as QA-SVM. To train this SVM classifier quantum annealer is utilized and the QUBO equation is utilized for energy cost minimization purposes, for results improvement some features of quantum annealing are also utilized. In another study, Silva et al. (da Silva et al., 2016) proposed quantum neural network architecture, their study also proposed a superposition-based learning algorithm with polynomial time. A support vector machine binary classifier that runs on a quantum computer and works based on a non-sparse matrix with a large number of samples and different features with logarithmic complexity is presented (Rebentrost et al., 2014). Different quantum ML approaches are presented in table 1.

4. QUANTUM NEURAL NETWORKS

Classical deep neural networks have gained increased intention in the last decade and are the most important and well-known tools for machine learning. Many computer vision and medical image processing tasks have been solved by using these deep networks in different combinations (Amin, Sharif, Gul, Raza, Anjum, Nisar, et al., 2019; Amin, Sharif, Yasmin, et al., 2018; Amin, Sharif, Yasmin, Saba, Anjum, & Fernandes, 2019b; Anjum et al., 2020; Fayyaz et al., 2020; Hussain et al., 2020; Naqi et al., 2020; Raza et al., 2018). Deep feed-forward networks are the most basic example of classical deep NNs and can mathematically be defined as in equation 6:

$$B = f\left(A;\theta\right) \tag{6}$$

Here A representing the input vector of n-dimensions, B is generated output vector of m-dimensions and theta is representing the basic parameters for mapping the input vector to the output vector (Goodfellow et al., 2016).

Table 1. Summary of the existing work

Authors	Year	Type	Nature of Task	Model Name	Research Area
(Willsch et al., 2020)	2020	Quantum	Optimization & Classification	QASVM	Applied on Both Synthetic & Real Biomedical Data
(Sagheer et al., 2019)	2019	Q-Inspired	Classification	AMP	Breast & Synthetic Data
(Ruan et al., 2017)	2017	Hybrid	Classification	Quantum KNN	MINIST Data
(Schuld et al., 2016)	2016	Quantum	Regression	Quantum Regression	-
(Lu & Braunstein, 2014)	2014	Hybrid	Classification	TNN & MERA	MNIST & Synthetic Data
(Benedetti, Garcia-Pintos, et al., 2019)	2019	Hybrid	Generative Model	DDQCL	Synthetic BAS Data
(Tiwari & Melucci, 2018)	2018	Q-Inspired	Classification	QIBC	Text & Image Data
(Adhikary et al., 2020)	2020	Hybrid	Classification	Single-Shot Training	Iris, Cancer & Sonar Detection
(Sergioli et al., 2019)	2019	Q-Inspired	Classification	QNMC	Medical Data
(Bishwas et al., 2019)	2019	Q-Inspired	Clustering	Quantum SVM for Clustering	Big Data
(Huang et al., 2021)	2021	QML	Prediction	Projected Quantum Model	Engineered Dataset
(Pomarico et al., 2021)	2021	Q-Inspired	Classification	Quantum SVM	Breast Cancer Biomedical
(Gupta et al., 2021)	2021	QML	Prediction	QML and Deep Models	Diabetes Detection
(Houssein et al., 2021)	2021	QML	Classification	Quantum CNN	COVID-19 Detection
(Terashi et al., 2021)	2021	QML	Classification	Quantum Approach	Physics
(Sajjan et al., 2021)	2021	QML	Classification	Quantum Model	Eigen State Filtration

The development of deep quantum learning algorithms is mainly inspired by classical NNs. The Boltzmann algorithm is the simplest example of QNNs. Quantum computing algorithms have several advantages as compared to their classical counterpart for example an exponential speedup and better performance may be achieved by making accurate training (Chowdhury & Somma, 2016; Temme et al., 2011; Yung & Aspuru-Guzik, 2012).

Back groundwork in the quantum neural network was started in 1995, Kak tried to implement a classical NN in a quantum network (Kak, 1995). In his work a detailed discussion of the versatility of quantum neural computers was presented. In another study, Parus (Perus, 1996) proposed a quantum counterpart of the classical gradient descent method and presented parallelism in quantum computing while Menneer and Narayanan proposed quantum neural network architecture and also discussed the quantum theory (Menneer & Narayanan, 1995). Recent notable work in QNNs that shows the importance of QC is presented in (Cao et al., 2017; Sagheer et al., 2019; Wiebe et al., 2015; Zidan et al., 2019).

5. APPLICATIONS

QML is an emerging technology and is being applied at a large scale to automate different tasks. QML has many advantages as compared to classical machine learning for example it can handle big data efficiently and may produce exponential speedup in many tasks. Many real-world problems may effectively be solved by using QML that are difficult to solve with classical computing for instance big data classification (Rebentrost et al., 2014). QML can effectively be applied in the medical domain, image compression, forecasting series, and spam detection (Sagheer et al., 2019; Sergioli et al., 2018; Xia & Kais, 2018). It can also be utilized to solve scheduling and different classification problems with high accuracy and speedup (Havlicek et al., 2019; Schuld & Killoran, 2019; Tran et al., 2016). QML has applications in different domains such that cervical cancer detection (Iliyasu & Fatichah, 2017), classification of electro cardiac signals (X. Tang & Shu, 2014), decision making in games (Clausen & Briegel, 2018), speech recognition (Kafian et al., 2018), image classification (Ruan et al., 2017; Tiwari & Melucci, 2018), recommender systems and (Kerenidis & Prakash, 2016; E. Tang, 2019), and natural language processing. From the above discussion, it can be concluded that quantum computing can effectively be utilized to solve complex and high computational tasks specifically in the medical field for automatic disease detection. Due to the high speed and efficiency of quantum computation, it can effectively be utilized in real-time applications.

6. CONCLUSION

This study presented a comprehensive review of quantum machine learning with its importance, applications, current state, and building blocks. QML is an emerging technology that may effectively be used to enhance performance and to achieve exponential speedup in many tasks where classical computational methods have some limitations. The main objective of this study is to highlight the current work in QC including three categories pure QML, quantum-inspired ML, and hybrid ML. With the development of quantum research and theories, it may be inferred that quantum machine learning is best suited for the high computational task with a large amount of data that needs a level of parallelism. As research in the field of QML is making progress it can be inferred that better quantum computers and a quantum version of machine learning algorithms may be produced to solve complex tasks efficiently in the near future. Discovering better algorithms to work with quantum computing is still an open area of research. Finally, this study gives an overview of quantum machine learning and recent studies in quantum computations with its possible applications. In future this work can be extended to provide a deeper view of quantum machine learning algorithms implementation on real quantum machines. Moreover, domain specific survey such that application of QML in medical diagnosis system may also be investigated.

Table 2. List of abbreviations

ML	Machine Learning
QNN	Quantum Neural Network
QML	Quantum Machine Learning
AI	Artificial Intelligence
KNN	K- nearest Neighbor
Q-inspired	Quantum inspired
QC	Quantum Computing
SVM	Support Vector Machine

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