A study on deep learning algorithms with and without quantum computing

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Abstract— There is exponentially growth of data globally which calls the need for effective and efficiency technology though there have been attempts to mitigate that by the introduction of MapReduce and Hadoop under the classical machines.

The era of quantum supremacy is around the corner thus Quantum Machine Learning (QML) is a viable successor to machine learning. The main advantage of quantum computers is that they can perform highly complex operations with exponential speedups. Thus, they have the capability to solve problems mostly that are not currently feasible.

This study seeks to explore the possibilities of QML that is a combination of Machine Learning (Deep Learning) and Quantum Physics by comparing deep learning algorithms with and without quantum computing taking special consideration to the parameters such as accuracy and time taken to crunch a dataset in both methods separately.

Keywords—*machine learning; deep learning; quantum computing; quantum machine learning.*

I. Introduction

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks **Brownlee [1]**. The rapidly evolving technology has also brought about the rapidly increase of data to be processed. Hence, this has spearheaded for better solutions to process the data such as the hot topic of Quantum Machine Learning (QML) which is a combination of machine learning and quantum physics (mechanics). Quantum Physics is the body of scientific laws which is the study of physical phenomena that happen at the atomic or subatomic level. It basically, outlines the odd behavior of atoms, photons and the other particles that make up the universe. Atoms are stated to exist as simultaneously decayed or un-decayed state until a measurement forces it into an exact state. This scenario is described as a superposition until that system is measured.

Machine Learning (ML) is the sub-area of artificial intelligence (AI) which refers to the ability of computer systems to independently find solutions to problems by recognizing patterns in databases **Klass [2]**.

ML grants the ability for computer systems to recognize patterns on the basis of existing algorithms and data sets and to develop adequate solution concepts. Therefore, in Machine Learning, artificial knowledge is generated on the basis of experience.

In order to enable the software to independently generate solutions, the prior action of people is necessary. For example, the required algorithms and data must be fed into the systems in advance and the respective analysis rules for the recognition of patterns in the data stock must be defined. Once these two steps have been completed, the system can perform the following tasks by Machine Learning:

- Finding, extracting and summarizing relevant data
- Making predictions based on the analysis data
- Calculating probabilities for specific results
- Adapting to certain developments autonomously
- Optimizing processes based on recognized patterns

ML is run in the conventional computers.

1.1 Types of Machine Learning

According to **L'heureux et al [3]** there are several types of machine learning namely:

- Supervised learning
- Unsupervised learning
- Reinforcement learning

A. Supervised learning

It is the learning in which we teach or train the machine using the data which is well labelled that means some data is already tagged with the correct answer.

It performs tasks such as regression to do weather and market forecasting and as well as tasks like classification for identity fraud detection and customer retention.

B. Unsupervised learning

It is the training of machine using information that is neither classified nor labeled and allowing the algorithm to act on that information without guidance.

This is used for clustering to perform tasks such as market segmentation and for recommender systems. And as well perform tasks such as dimensionality reduction for big data visualization and meaningful compression.

C. Reinforced Learning

It is a type of machine learning technique that enables an agent to learn in an interactive environment by trial and error using feedback from its own actions and experiences.

It is used to perform tasks such as real time detection, robot navigating, skill acquisition game AI.

1.2 Type of Machine Learning and their uses

The diagram below shows examples of tasks that's can be performed by the types of ML.

MACHINE LEARNING						
Supervised Learning		Unsupervised Learning		Deep Learning (semi - supervised)		
Regressors	Classifiers	Dimension Reducers	Clustering Methods	Unsupervised Pretrained Networks	Convolutional Neural Networks	Recurrent Neural Networks
Wireline log prediction Spatial interpolation Sesimic inversion (with numeric labels)	Automatic facies prediction from Wireline logs Seismic inversion (with categorical labels)	Compressing high dimensional data Incresing signal-to-noise ratio in data	AVO class prediction Seismic inversion (uncalibrated)	Seismic denoising Seismic multiple removal Seismic migration	Seismic structural feature / fault detection Automatic facies prediction from borehole imagery	Microseismic analysis Sedimentary process modelling Earthquake prediction

Fig 1.1: Types of Machine Learning and their uses.

As highlighted by the above diagram under supervised learning there are regressors which have an output variable that is a real or continuous value, such as "salary" or "weight". There's also classifiers which help identify similar objects for example, a classification algorithm will learn to identify animals after being trained on a dataset of images that are properly labelled with the species of the animal and some identifying characteristics.

Under unsupervised learning there is dimension reducers which is the process of reducing the number of random variables under consideration, by obtaining a set of principal variables. It can be divided into feature selection and feature extraction. On another hand there is clustering methods which is the process of organizing objects into groups whose members are similar in some way.

Lastly, deep learning there is unsupervised pretrained networks, convolutional neural network is a class of deep neural networks, most commonly applied to analysing visual imagery and recurrent neural network which is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence.

2.1 From classical to quantum

Classical computers are built using transistors and the data is stored as binary (0 and 1) which easily make them less superior than the Quantum computers which are built with subatomic particles referred to as quantum bits, in short qubits. These qubits are superposition in nature that is they can be in multiple states at the same time. So, by the virtue of quantum computing being superior, it is deemed as the right possible replacement for classical computers.

Quantum is a word that originated from the Latin for "how much". It shows that quantum models always involve something coming in discrete amounts. This basically means that Quantum is the minimum amount of any physical entity involved in an interaction.

2.2 Quantum Computing

As discussed above QC makes use of qubit which is described as a vector in a two-dimensional Hilbert space**.** Qubit is a unit of quantum information that has two basis states, which are $|0>$ and $|1>$ **Hagouel and Karafyllidis [4].** This therefore puts it in a superposition state:

$$|0> = [10] \quad |1> = [01]$$

Superposition is a state whereby quantum particles or qubits exist as both 0 and 1 simultaneously. Thus, a particle exist in multiple quantum states hence when there is an attempt to measure its position it will go through change losing its superposition.

Therefore, a superposition of qubit $|\psi>$ can be represented in any combination of the two states:

$$|\psi> = a|0> + b|1>$$

Where, a and b are called probability amplitudes also referred to as complex numbers. When measuring a superposition qubit, the measurement outcome is 0 with probability $|a|^2$ and 1 with probability $|b|^2$. Hence, $|a|^2 + |b|^2 = 1$.

A number of qubits are referred to as a quantum register, it is a vector in multi-dimensional Hilbert space. The aspect of quantum register brings in the aspect of quantum entanglement. Entanglement is when the particles are separated by a large distance but they still communicate with each other in a correlated manner. This concept of entanglement process information in ways that cannot be done in conventional machines **Biamonte et al [5]**. Thus, different qubits interact with each other on an atom in a way that the state of one particle cannot be described independently of the other particles.

Quantum register are acted upon or manipulated by the quantum gates which are unitary operators of the Hilbert space **Hagouel and Karafyllidis [4].** It change the quantum state of qubits or quantum registers. Quantum gate map a quantum states onto other quantum states.

II. APPICATION OF QUANTUM MACHINE LEARNING

A combination of machine learning and quantum computing is referred to as the Quantum Machine Learning (QML). It is projected to bring about future benefits in various fields such as below:

- Healthcare – by simulating molecules to make new drugs and new materials.
- Military – to ensure a secure communication channel with improved encryption.
- Machine learning – improve the algorithms which in turn speed up discoveries for instance in medical for better and faster illness diagnoses.
- Cyber security – it will make it difficult to hack systems.
- Business – by simulating economic forecast and complex risk analysis

III. LITERATURE ANALYSES

A comparison of classic Relief algorithm (Relief), classic ReliefF algorithm (ReliefF), quantum Relief algorithm (QRelief) and quantum ReliefF algorithm (QRliefF) was conducted by **Chen et al [6]** under the terms of complexity of similarity calculation (CSC), complexity to find the nearest neighbour (CFNN) and Resource consumption (RC). This study demonstrated that the relief and ReliefF are similar in terms of CSC, CFNN and RC as they both had same results of O(MN), O(M) and O(MN) bits respectively. The QRelief and QReliefF are slightly similar as they both had a CSC and RC of O(M) and O(MlogN) qubits respectively. The difference of the two was that the

QRelief had a CFNN of O(M) and the QReliefF had a CFNN of O(√M). The QRelief and QReliefF algorithms proved to be fast as compared to other algorithms under study. This is so because they use quantum bits which can store 2n information thereby giving it a superior storage capacity. However, the QReliefF proved to be of more superior as it use quantum Grover method to find k nearest neighbor samples which makes it exponential faster.

Bishwas et al [7] demonstrated that a classical algorithm can be implemented in a quantum computer by adjusting the same measure model. The proposed algorithm (Quantum K-means algorithm)'s runtime complexity at different stages was analysed in comparison with the conventional classical computer. A fair comparison was drawn and depicted that the proposed quantum K-means algorithm was has exponential speedup up as compared to classical algorithm.

A quantum neural network algorithm (QNN) algorithm was applied to a research conducted by **Bouchti et al [8]** on a case study of Moroccan companies' financial risk. The QNN financial risk model enhanced the financial prediction efficiency and the computing time.
However, it had some drawbacks such as the selection of the index was restricted, excluding some of the non-financial aspects and choosing a small sample could possibly affect the model in a certain way.

Amin et al [9] used a quantum Boltzman algorithm under supervised machine learning were by they managed to attain an accuracy of 96, 2%. Hence, this paves new possibilities to quantum information processing and machine-learning research areas.

A deep learning approach was employed for vegetation cover mapping by **Nijhawan et al [10]** taking the data of Uttarakhand State, a comparable accuracy of 88.43 % was attained. The approach outperformed other state-of-art algorithms. Hybrid of CNN when integrated with handcrafted (LBP+GIST) features proves to be an efficient framework for mapping vegetation cover area. The framework can be employed in the surrounding regions with similar topographic environment.

Gupta et al [11] represented the concept of QML in an application with Big Data and Artificial Networks. The main advantage of the Quantum Learning Algorithm is the ability to react and adapt independently in Classical as well as in the Quantum environment. The availability of Open Quantum Systems provides beneficial for QML as it paves way for more technological advancements. This also depicts the introduction of Quantum Access Memories to cope up with the increasing demand of Quantum Algorithms.

A hospital's structured data and unstructured data was used with **Hao el al [12]** in a convolutional neural network based multimodal disease risk prediction (CNN-MDRP). They brought to light that during the time of the study under the area of medical big data analytics there existed no work on the study of both structured and unstructured data. The proposed algorithm was compared against several algorithms and had an accuracy of 94.4%. It also had a convergence speed faster than the CNN-based unimodal disease risk prediction (CNN-UDRP) algorithm.

Dasgupta and Singh [13]'s proposed CNN model had an accuracy of 95:33% accuracy and 0:974 AUC score.3 on DRIVE dataset as it outperformed state of the art for automatic retinal blood vessel segmentation. The retinal diseases diagnosis is performed by undertaking a vital process of automatic segmentation of retinal blood vessels from fundus images. This however faces some challenges such as extreme variations in morphology of the vessels against noisy background. This study attempts to mitigate the challenges by formulating the segmentation task as a multi-label inference task and utilize the implicit advantages of the combination of convolutional neural networks and structured prediction.

This study on convolution neural network (CNN) architectures and the learning methods on object categorization (ILSVRC) problem was done by **Mishkin et al [14]** as they critically scrutinised the impact of the recent advances. They took into consideration various choices such as those of the architecture: non-linearity (ELU, RELU, max-out, compatibility with batch normalization), pooling variants (stochastic, max, average, mixed), network width, classifier design (convolutional, fully-connected, SPP), image pre-processing, and of learning parameters: learning rate, batch size, cleanliness of the data.

The proposed modifications' performance gains are tested first individually and then in combination. The results attained showed that the sum of individual gains is greater than the observed improvement when all modifications are introduced, but the "deficit" is small suggesting independence of their benefits.

The automated pavement crack detection is quite vital as it paves way in avoiding several accidents from occurring **Zhang et al [15]**. The massive inhomogeneity nature of cracks makes this area of study difficult and presents many problems for instance the surrounding pavement might have a low contrast which gives a complex background.
In this research an attempt to counter this challenges is undertaken by training a deep CNN to categorise every image cracks in the dataset. The deep learning framework under study provided superior results as it was able to perform crack detection with better accuracy as compared to the use of existing hand-craft methods to extract features.

Two efficient approximations to standard convolutional neural networks: Binary-Weight-Networks and XNOR-Networks were proposed by **Rastegari et al [16]**. In Binary-Weight-Networks, the filters are approximated with binary values resulting in 32× memory saving. In XNOR-Networks, both the filters and the input to convolutional layers are binary. XNOR-Networks approximate convolutions using primarily binary operations. This results in 58× faster convolutional operations (in terms of number of the high precision operations) and 32× memory savings. XNORNets offer the possibility of running state-of-the-art networks on CPUs (rather than GPUs) in real-time. They binary networks are simple, accurate, efficient, and work on challenging visual tasks. Hence evaluated their approach on the ImageNet classification task. The classification accuracy with a Binary-Weight-Network version of AlexNet is the same as the full-precision AlexNet. Therefore they compare their method with recent network binarization methods, BinaryConnect and BinaryNets, and outperform these methods by large margins on ImageNet, more than 16% in top-1 accuracy.

Andriyash et al [17] proposed that quantum computing provides many possibilities for the Boltzmann machines. The proposed quantum methods illustrated that quantum computing is better for optimisation of the objective function under study, it reduces the time to train and offers a better richer framework for deep learning as compared to the classical computer.

Sinayskiy and Petruccione [18] they examined the possibility of training a quantum Boltzmann machine (QBM). However, unlike the classical BM, for which the gradients of the log-likelihood can be estimated using sampling, the existence of a transverse field in the QBM makes the gradient estimation nontrivial. We have introduced a lower bound on the log-likelihood, for which the gradient can be estimated using sampling. We have shown examples of QBM training through maximizing both the log-likelihood and its lower bound, using exact diagonalisation, and compared the results with classical BM training.
Finally, the possibility of using a quantum annealer for QBM training was examined. Although the current commercial quantum annealers like D-Wave are not designed to provide quantum Boltzmann samples, with minor modifications to the hardware design, such a feature can become available. This would open new possibilities in both quantum information processing and machine 6+learning research areas.

Wiebe et al [19] described an algorithm for a universal quantum computer to implement a linear regression model for supervised pattern recognition. The quantum algorithm reproduces the prediction result of a classical linear regression method with (unregularised) least squares optimisation, thereby covering an important area of machine learning. It runs in time logarithmic in the dimension N of the feature vectors as well as independent of the size of the training set if the inputs are given as quantum information. Instead of requiring the matrix containing the training inputs, X, to be sparse it merely needs X†X to be representable by a low-rank approximation. One can furthermore transform the input data by a nonlinear feature map known as the "kernel trick" to increase the potential power of the method. The application of different kernels as well as the question of how to include regularisation terms is still open for further research. The sensitive dependency on the accuracy as well as the unresolved problem of state preparation (which appears in any of the numerous quantum algorithms encoding classical information into the amplitudes of quantum states), illustrate how careful one needs to treat 'magic' exponential speedups for pattern recognition. However, as demonstrated here, quantum information can make a contribution to certain problems of machine learning, promising further fruitful results in the emerging discipline of quantum machine learning.

Quantum perceptron can be trained in two possible ways in a quantum computer as proposed by **Kapoor et al [20]**. The first provides quadratic speedups depending with the size of the training data. This algorithm was illustrated to be asymptotically optimal as it would violate the known lower bounds for quantum searching if a super-quadratic speedup was to be possible. The second on provides quadratic reduction in the scaling training time with the margin between the two classes it constitutes a quartic speedup relative to the typical perceptron training bounds that are usually seen in the literature. The conclusion done for both models was that they all have quadratic speedups which is essential to machine learning. **Kapoor et al [20]** advocated that the undertaking of a deeper study of quantum models separate from classical models can lead to the discovery of new opportunities in the quantum computing world.

Shang et al [21] brought to light the major problem with machine learning algorithms which is of manipulating and classifying large numbers of vectors in high dimensional spaces. This problem is countered in quantum computing due to its ability to manipulate vectors in multi-dimensional space.

This paper explains the origin and of meaning qubit, quantum register, quantum gates, and the application of quantum information in the quantum computing world. It goes on to show that the quantum algorithms have exponential speed which is used to enhance the KNN algorithm under study in this paper.

IV. PROBLEM FORMULATION

The exponentially growth of data globally calls the need for effective and efficiency technology to act upon the data. Thus, the following measures needs to be taken to counter the future problems of the rapidly growth of data.

The first one is to speed up the computation of machine learning tasks by devising efficiency ways to execute the big chunks data. This will reduce the computation time of machine learning tasks as the quantum computer has the ability to compute large vectors of data.

The second point is to enhance accuracy of the results in classical by applying quantum machine learning.

Finally, to do a research that could inspire other researchers and appreciate what quantum computing can bring. Quantum computer will open vast of opportunities in various industries namely military, medical field, agriculture. Banking and finance as it is capable of computing large chunks of data and deriving insights which is deemed impossible on conventional computers.

V. PROPOSED METHODOLOGY

The solution is based on the deep learning algorithm that will be first developed and executed on a classical machine and later on it will then be executed in the quantum simulator. A comparison will be made based on certain parameters such as time, accuracy and performance.

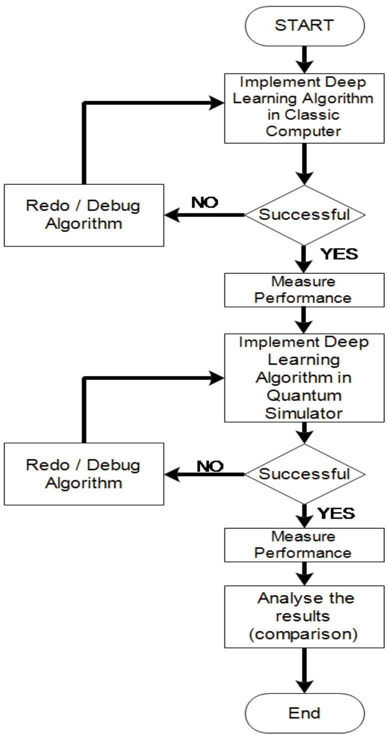

Fig 4.1: Flow diagram of the proposed system

VI. CONCLUSION

QML is a viable successor to machine learning as it is capable of performing highly complex operations with exponential speedups and to solve problems mostly that are not currently feasible with classical machine learning. QML will bring many benefits to various fields namely healthcare, military, cyber security and machine learning.

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