Deep learning algorithms with and without quantum computing

Arthur Kudakwashe Mupfumira[1], Astha Gautam[2], Keshav Kishore[3]
[1]*M.Tech (CSE), Research Scholar, Alakh Prakash Goyal Shimla University (H.P)*
[2]*Assistant Professor (CSE), Research Scholar, Alakh Prakash Goyal Shimla University (H.P)*
[3]*Head of IT, Alakh Prakash Goyal Shimla University (H.P)*
artmupf@gmail.com[1]
asthagautam@hotmail.com[2]
mails4keshav@gmaill.com[3]

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

Machine learning is still being used to derive insights from the big chunks of data. However, scientists believe ML will reach a time were by it will no longer efficient enough to process the big data. Hence, they are seeking ways to counter and in this case the proposed viable solution is that of QML.

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.

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.

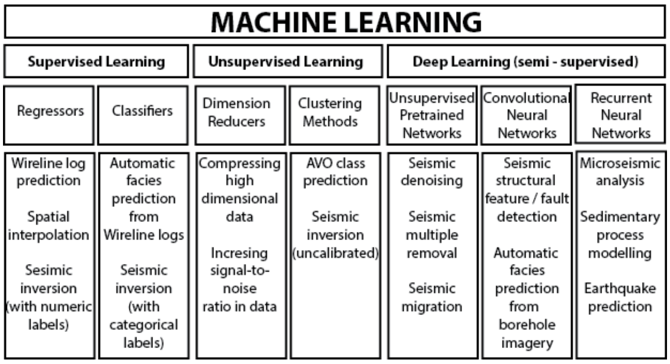

Fig 1.1: Types of Machine Learning and their uses.

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.

1.3 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.

1.3.2 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 ANALYSIS

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 $X^{\dagger}X$ 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. METHODOLOGY

5.1 Aim

The main aim of this study is to do a comparison of deep learning algorithm with or without quantum computing that is imperative to improving machine learning's accuracy, time complexity, and performance. To achieve this the aim of the study is broken into objectives below.

5.2 Objectives

The objectives of the study are:

- To speed up the computation of machine learning tasks,
- To compare the accuracy of the results in classical and quantum computing,
- To evaluate the overall performance between a classical and quantum computing,
- To do a research that could inspire other researchers and appreciate what quantum computing can bring.

5.3 Flow diagram of the proposed system

As highlighted in the Fig 5.1, 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.

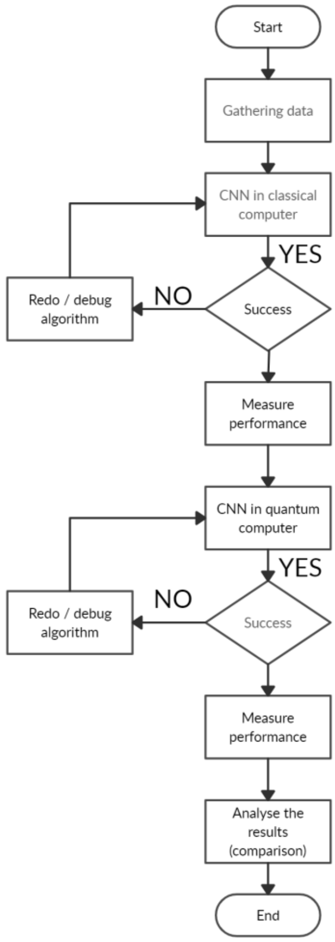

Fig 5.1: Flow diagram of the proposed system

- The first stage is of gathering data. In this phase the secondary method of data collection is used to gather information or data from different sources such as journal, research papers and internet. This gives a deeper understanding of the topic under study by the virtue of going through how other studies conducted a similar study.
- The second stage is implementing a deep neural network algorithm in classical computer. This is done so that later on a performance comparison can be carried about which algorithm is best between a classical and a quantum computer algorithm.
- Third stage comes after successfully implantation of a classical algorithm in a conventional machine. The

results achieved are first analysed individually as in only that of the conventional computer.

- Fourth stage, a deep neural algorithm is implemented in quantum computer. The results obtained here are analysed here and kept for later comparison with that of a conventional machine.
- Fifth stage comes after successfully implantation of a quantum algorithm in a quantum machine. The results achieved are first analysed individually as in only that of the quantum computer.
- Last stage, which is the most important part of the research. On this phase results obtained in executing a deep neural network in both a classical and quantum computer are analysed against each other to find out which one performed overall best.

VI. PROPOSEED WORK

6.1 Overview of the Proposed Work

The proposed system looks into two types of computer performance namely classical and quantum computer. A CNN algorithm is executed in both computers. This is discussed in detail below.

6.2 Convolution Neural Network Architecture

Convolutional Neural Networks (CNNs or ConvNets) belongs to the neural networks family and is used in classification and image recognition were it has successfully proved to be good in identifying objects and to analyse visual imagery. CNNs are used in vast areas namely in natural language processing, video and image recognition.

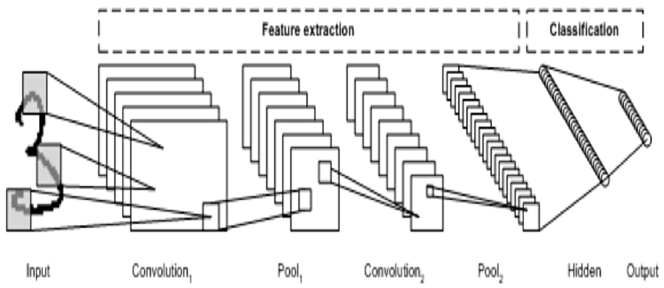

Fig 6.1: Convolution neural network architecture

CNNs have many layers which act on the input data which means more features to be extracted from the input. Its layers and functionality is given below:

- **Convolution layer:** It processes the input data using a filter or kernel to generate a feature map which help to place each feature in its class of belonging.
- **Pool layer:** Its main role is to downsize the size of information in each feature to make way for less time computation in the next layers in the network.
- **Fully Connected layer:** This layer receives input as an output from previous layers then flattens it and convert it into a single vector which will act as an input to the next stage

6.3 Classical Computer

Classical computer is a type of computer which stores information in bits. This bit is either on or off.

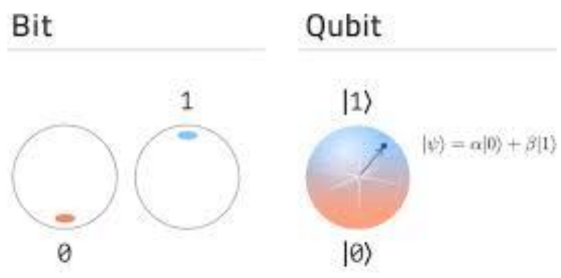

Fig 6.2: Bit VS Qubit

As shown in figure 6.2, the conventional computer its bit is either a 1 or a 0 never will it be in both states at the same time. Unlike bits, the qubit depicted by a sphere in figure 6.2 can be in both states of either being 1 or a 0 until it is measured.

As shown in figure 6.2, the conventional computer as bit is either a 1 or a 0 never will it be in both states at the same time. Unlike bits, the qubit depicted by a sphere in figure 6.2 can be in both states of either being 1 or a 0 until it is measured.

6.3.1 Executing CNN in a Classical computer

The CNN consist of two layers was used for performing the training. It is a sequential model which is a linear stack of layers. This is illustrated by the figure below:

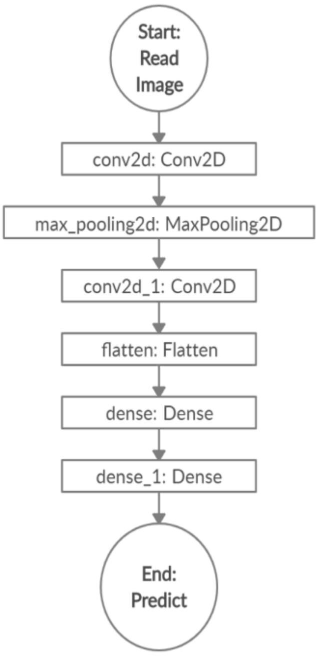

Fig 6.3: Classical neural network flowchart

The classical neural network is first initialized and layers are added using the add method.
Layers added are shown in the below table:

Layer	Parameters
Conv2D (2D Convolutional layer)	• filters = 32; • kernel size = 3 x 3; • activation function = relu; • input shape - 28 x 28
MaxPooling2D is a Max pooling operation for spatial data.	• pool size = 2,2,
Conv2D	• filters: 64; • kernel size = 3 x 3; • activation function = relu;
Flatten - This layer flattens the input. Does not affect the batch size. It is used without parameters.	
Dense	• Dense = 1
Dense	• Dense = 1

Table 6.1: Classical CNN parameters

The layers used in the CNN in this study is a Conv2D which consists of filters 32, kernel size of 3 x 3, activation function used is a relu and the input shape is input shape - 28 x 28 dimensions. A maxpool of 2x2 and a dense of 1.

6.4 Quantum Computer

Whereas, a quantum computer is a non-computer type in which date is represented as quantum bits (qubits). A qubit experiences a condition known as superposition were by a qubit can be on and off at the same time.

6.4.1 Quantum Neural Network Architecture

A quantum neural network model is implement in order to simulate the crunching of the dataset in a quantum computer.

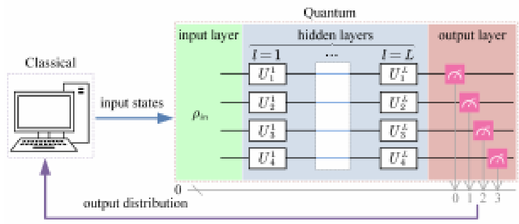

Fig 6.4: Quantum neural network flowchart

As shown in figure 6.2, the qubit depicted by a sphere can be in both states of either being 1 or a tate.0 until it is measured. This state of being neither a 1 nor a 0 is known as the superposition state.

6.4.2 Training Process in a Quantum Computer (Simulator)

The images are reduced to 4x4 pixels for them to fit into a quantum circuit. Developed a two qubit model which is then fitted into the keras model with quantum components. This model is fed the quantum data that encodes the classical data.

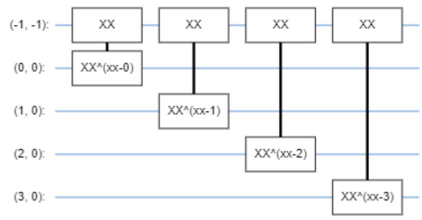

Figure 6.5: Quantum circuit layer

VII. EXPERIMENT AND IMPLEMENTATION

7.1 Facilities Required for Proposed Work

To carry out this study the minimum hardware required is a core i3 computer with a ram of at least 4 GB and the storage space it is not a necessity here as the study was carried out using cloud softwares.

The softwares required to carry out this study google colaboratory which was IDE of choice for this particular study. A google colaboratory was the chosen because of the following reasons:

- It supports python and its data science libraries,
- No need for set up,
- Computation power is provided for free so it eliminates the use of high cost laptops.

Python which is the base language which was used because of its compatibility with both the google laboratory and the tensorflow quantum.
Tensorflow quantum is used to simulate the quantum computer. Tensorflow quantum library will connect the laptop being used in this study to the google hybrid quantum computers.

7.2 Dataset

A good dataset consists of the following features:

- It has no missing values.
- Absent of aberrant data.
- It must be easy to manipulate (logical structure).

In this study a dataset containing approximately 10,000 28x28 grayscale images of 10 fashion categories, along with a test set of 3,000 images was used. The dataset was divided into a training set and test set with a ratio of 20%.

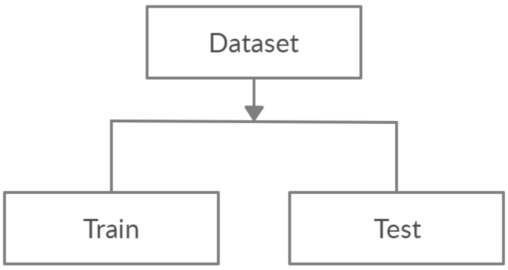

Fig 7.1: Division of Fashion Dataset for classification

The below figure shows different types of clothing. The various types of clothing are put in 10 fashion categories namely T-shirt/top, Trouser, Pullover, Dress, Coat, Sandal, Shirt, Sneaker, Bag and Ankle boot. An image of each class can be observed in the figure 7.2 below.

Fig 7.2: Images of fashion dataset

As shown by the table 7.1 below, the dataset consists of several categories classified into ten classes.

Label	Description
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot

Table 7.1: Fashion Dataset labels

VIII. RESULTS AND ANAYLSES

The overall performance results obtained showed that a conventional computer is better than a quantum computer at solving classical problems such as email and spreadsheets.

8.1. Results from a Classical CNN

The CNN algorithm was analysed in a classical computer and the results shown are depicted in the image below figure 8.1. This clearly brought to light that the classical computer is currently better than a quantum computer when it comes to processing of the classical data. This was so because in this study the classical computer was able to surpass the quantum computer with an accuracy of 90%, validation accuracy of 87%, loss of 27% and validation loss of 35%.

```
Train on 9000 samples, validate on 1000 samples
Epoch 1/3
9000/9000 [==============================] - 6s 657us/step - loss: 0.2772 - accuracy: 0.9020 - val_loss: 0.4995 - val_accuracy: 0.8190
Epoch 2/3
9000/9000 [==============================] - 6s 644us/step - loss: 0.2616 - accuracy: 0.9049 - val_loss: 0.3823 - val_accuracy: 0.8730
Epoch 3/3
9000/9000 [==============================] - 6s 644us/step - loss: 0.2696 - accuracy: 0.9047 - val_loss: 0.3458 - val_accuracy: 0.8740
1000/1000 [==============================] - 0s 280us/step
```

Fig 8.1: Results obtained after training in a classical CNN

The figure 8.1 shows the loss, loss accuracy, accuracy and validation accuracy of the CNN in a classical computer. The results obtained here were clearly shown in the table 8.1.

	Epoch (1/3)	Epoch (2/3)	Epoch (3/3)
Loss	28	26	27
Accuracy	90	90	90
Validation Loss	50	38	38
Validation Accuracy	89	87	87

Table 8.1: Results obtained after training in a classical CNN

8.1.2 Confusion Matrix for Classical CNN

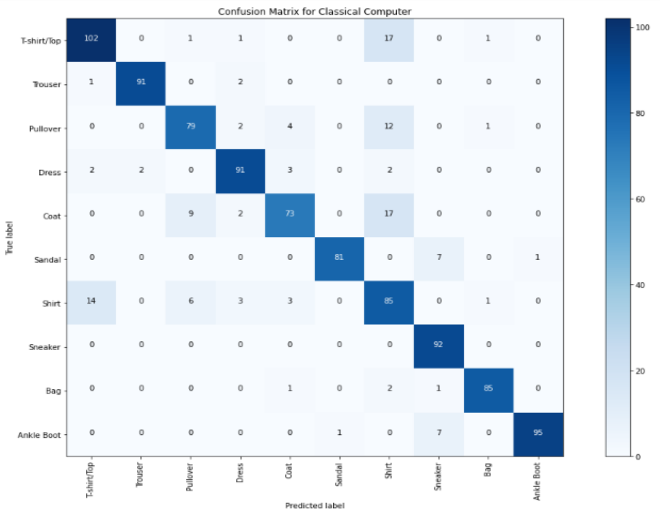

Fig 8.2: Confusion Matrix for Classical CNN

A confusion matrix which is also known as the error matrix is a statistical classification which is a table used to describe the classification model performance on a set a set of data with known values. It also gives the visualization on the performance of the algorithm thereby providing easyidentification of confusion between classes for instance were by one class is commonly mislabelled as the other class.

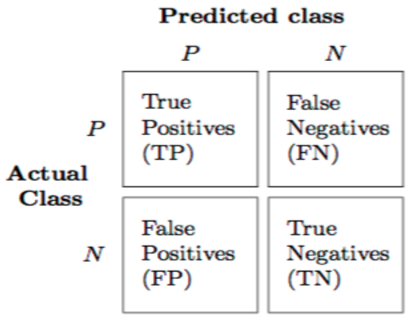

Fig 8.3 Confusion matrix

In the figure 8.3, it shows that TP (True Positive) means the observation is positive and is predicted as positive, FP (False Positive) means observation is positive but is predicted as negative, TN (True Negative) means the observation is negative and is predicted as negative and FN (False Negative) means the observation is negative but it is predicted as positive. This makes it a two dimensional matrix where each row represents the instances in predictive class while each column represents the instances in the actual class or you put the values in the other way.

- Accuracy : $\frac{(TP+TN)}{(TP+TN+FP+FN)}$
- Precision: $\frac{(TP)}{(TP+FP)}$
- Recall formula: $\frac{(TP)}{(TP+FN)}$
- Score formula: $\frac{2*(Precision*Recall)}{(Precision+Recall)}$

Key

- **True Positive -** is the actual predicted image class that was successfully classified.
- **False Positive -** is the type of image wrongly classified as the actual image type.
- **True Negative –** relates to other classes that do not belong to the actual class.
- **False Negative -** relates to actual class category that was wrongly classified and did not belong to the actual class.

In this study, the confusion matrix in a classical computer was able to classify the data of the fashion dataset which consist of clothes into their respective categories better than the confusion matrix in the classical computer. This is depicted in figure 8.2, which has less misplaced clothes as compared to the quantum confusion matrix in figure 8.5.

8.2 Results obtained from a Quantum CNN

The figure below shows that a quantum computer is currently being outclassed by a classical computer. In this study it achieved an accuracy of 84%, validation accuracy of 42%, loss of 44% and an out of the range validation loss which are all less than that of a classical computer.

```
Train on 9000 samples, validate on 1000 samples
Epoch 1/3
9000/9000 [==============================] - 13s 1ms/step - loss: 0.8433 - accuracy: 0.7257 - val_loss: 2.4828 - val_accuracy: 0.1110
Epoch 2/3
9000/9000 [==============================] - 6s 648us/step - loss: 0.5175 - accuracy: 0.8179 - val_loss: 2.3798 - val_accuracy: 0.1210
Epoch 3/3
9000/9000 [==============================] - 6s 648us/step - loss: 0.4440 - accuracy: 0.8379 - val_loss: 2.1990 - val_accuracy: 0.4210
1000/1000 [==============================] - 0s 393us/step
```

Fig: 8.4: Results obtained after training in a quantum neural network

The figure 8.4 shows the loss, loss accuracy, accuracy and validation accuracy of the CNN in a quantum computer. The results obtained here were clearly shown in the table 8.2.

	Epoch (1/3)	Epoch (2/3)	Epoch (3/3)
Loss	84	52	44
Accuracy	72	81	83
Validation Loss	248	237	219
Validation Accuracy	11	12	42

Table 8.2: Results obtained after training in a quantum CNN

6.2.1 Confusion Matrix for Quantum CNN

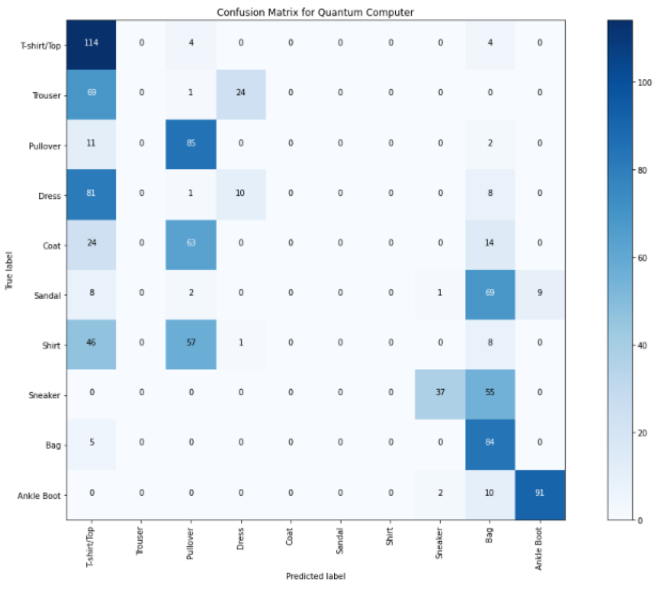

Fig 8.5: Confusion Matrix for Quantum CNN

As shown in figure 8.5, the confusion matrix in a quantum computer was beaten by that of a conventional computer as it had so many misplaced data. This brings to light that currently at the moment the classical computer out performs the quantum computer when it comes to executing of the classical data.

8.3 Results comparison of overall performance between Classical VS Quantum Computer

The main aim of a quantum computers is to obtaining a considerable speed up of the computation process. But however the below figure 8.6 shows that currently the classical computer outperforms the quantum computer. With classical data it is difficult for a quantum computer to beat a conventional computer.

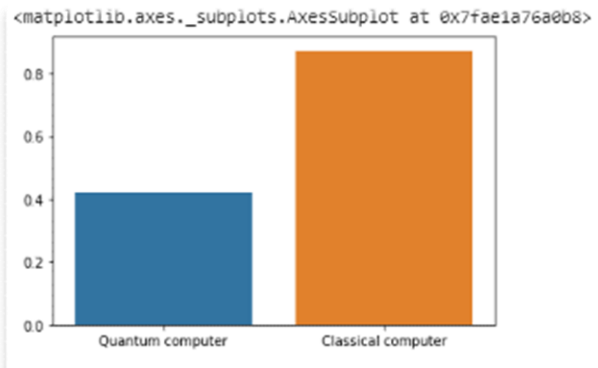

Fig 8.6: Results of Classical VS Quantum neural network using tensorflow

The overall evaluation comparison between the quantum and the classical computer is shown in figure 8.6 which depicts how the approximate percentage of how far a classical computer outperforms the quantum computer. Bernard Marr "Classical computers are better at some tasks than quantum computers (email, spreadsheets and desktop publishing to name a few). The intent of quantum computers is to be a different tool to solve different problems, not to replace classical computers".

IX. CONCLUSION

Quantum computing has great potential of solving many problems of humanity by achieving a performance far superior to today's computers. Although no cases have been demonstrated in which quantum computing exceeds the classical computing in a specific task (quantum supremacy), scientists in this area ensure that we are close. In this work, we set out to understand how these types of algorithms work and how it is possible to convert conventional to quantum algorithms.

In this study the experiments were performed in quantum cloud services and quantum computing simulators. The results attained were superior in the classic solutions. The contribution of this work focuses on attempt to speed up machine learning tasks.

X. FUTURE SCOPE

Although the results were not competitive, there are some lessons learned that could reduce the learning curve of future implementations. Techniques that allow the best selection and reduction of features are indispensable for this limited environments. The quantum machines available in the cloud have a system of task queuing, so executions can take a long time, not because of the processing time, but because of the ability of these devices to prepare and dispatch the queued processes. It is important to note that emulators consume large amounts of memory, which depends on the information entered. It is important to make tests with different volumes of data to prevent memory saturation.

It is not yet clear what type of implementations are the most benefited from the use of quantum machine learning. Future work can perform a comparison of techniques by different areas and find which front is closest to the quantum supremacy. This can lead future research work to create a simple baseline for experimentation.

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