International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Binary Image Classification on Fashion-MNIST Using TensorFlow-Quantum and CIRQ

Prabhakar Kandukuri[1], Dasari N. V. Syam Kumar[2], V. Sesha Srinivas[3], Chilukala Mahender Reddy[4] and Kranthi Kumar Singamaneni [5*]

Submitted: 27/08/2023 **Revised**: 22/10/2023 **Accepted**: 02/11/2023

Abstract: TensorFlow and Cirq, two key Google frameworks, are used to process the binary image classification on the dataset. These frameworks were developed by Google. The binary image classification is utilized most frequently in the process of distinguishing an object from its background. The process of segmentation makes it possible to name each pixel as either background or object and then assign black and white colors that match to those labels. The combination of machine learning with quantum computing will lead to a classification that is superior to that achieved by machine learning classification techniques. The TensorFlow Quantum (TFQ) library is a quantum machine learning framework that enables quick prototyping of hybrid quantum-classical ML models. This method proposes using the TFQ library. In order to process the categorization, QNN and CNN are both used as algorithms. Existing challenges for binary image classification include overfitting, a limited amount of data, variability in picture data, and background noise. These challenges are all interrelated. The quantum machine learning methodology that has been developed has the potential to reduce problems such as variability in image data, optimize the background noise that has been discovered in the images, and minimize the overfitting that occurs in the image data.

Keywords: *TensorFlow-Quantum, CNN, QNN, Cirq*

1. Introduction

Binary image classification is a popular task in machine learning where the goal is to classify images into two distinct classes. The Fashion MNIST dataset, which contains images of clothing items, is a popular benchmark dataset for binary image classification tasks. Recently, researchers have been exploring the usage of quantum computing techniques to progress the accuracy and speed of image classification tasks. TensorFlow-Quantum (TFQ) is a library developed by Google that allows the integration of quantum computing into TensorFlow, a popular machine-learning framework. TFQ offers a great-level API for building and training quantum machine learning models, making it easier for researchers and developers to experiment with quantum algorithms [5]. Cirq is another quantum computing-based open-source library that provides a low-level API for designing and implementing quantum circuits. Cirq allows for more fine-grained control over the underlying quantum hardware, making it well-suited for evolving and challenging new quantum standards.

1Department of Artificial Intelligence and Machine Learning, Chaitanya Bharathi Institute of Technology – Hyderabad, India.
2Department of Computer Science and Engineering, Bapatla Engineering College, Bapatla, India
3Department of Information Technology, R.V.R & J. C. College of Engineering, Guntur, AP, India
4Department of Computer Science and Engineering, GITAM Deemed to be University, Hyderabad, India
5Department of Computer Engineering and Technology, Chaitanya Bharathi Institute of Technology, Hyderabad, India.
**Corresponding author:kkranthicse@gmail.com*

By combining the power of TensorFlow-Quantum and Cirq, researchers can build and train quantum machine learning models for binary image classification tasks on Fashion MNIST. These models have the potential to achieve higher accuracy and faster training times than classical machine learning models, leading to new breakthroughs in image classification and other related fields. This methodology has been proposed to identify the processing difference between the classical and the quantum machine learning techniques [3][5] [12-13]. The quantum machine learning techniques that are used like TensorFlow-quantum and the Cirq are producing quite optimal results than compared to the generational classical machine learning techniques. In this project we are trying to impose the quantum machine learning techniques on the FASHION MNIST dataset to show optimal and faster results than the classical machine learning techniques. The accuracy result is presented which led to the proof that the quantum machine learning techniques produce optimal and faster processing of the data than compared to the classical machine learning techniques [5]. TensorFlow is a framework by Google to implement machine learning algorithms and is suitable for an optimal implementation of quantum algorithms. Cirq is a software library written in Python that allows users to not only create, manipulate, and optimize quantum circuits, but also run those circuits on quantum computers and quantum simulators. The proposed method is expected to efficiently classify the binary images using quantum and machine learning integration. The proposed QML model optimizes the issues addressed and the binary image classification is efficiently displayed with optimal segregation of the unwanted background noise and the variability in the image data which most of the existing ML models fail to optimize [13-15]. The proposed methodology is an evaluation of the traditional machine learning techniques (TML) and the novel quantum machine learning (QML) technique to measure the optimality that the models produce. A QML library called TensorFlow Quantum (TFQ) is suggested in this method for quick prototyping of amalgam quantum TML. Standards from QNN and CNN are employed to process the classification. These models have the potential to outperform traditional machine learning models in terms of accuracy and training timeframes, opening the door for new developments in image categorization and related domains. The processing variances among TML and QML approaches have been identified using this methodology

2. Overview of Technologies

2.1. Classical Machine learning

The discipline of machine learning known as “classical machine learning” develops and trains machine learning models using traditional computing methods. Data is often represented in classical machine learning using classical bits, which can have values of 0 or 1. There are several different categories of traditional machine learning algorithms, including reinforcement, unsupervised, and supervised. The machine learning model is trained on labelled data in supervised learning, where the right output is provided for each input. Unsupervised learning aims to find patterns and structures in the data by training the machine learning model on unlabeled data. Reinforcement learning involves rewarding good behavior and punishing bad behavior, allowing the machine learning model to learn through trial and error. Natural language processing, driverless cars, image and audio recognition [5,], and many more fields make extensive use of traditional machine learning algorithms. They are also used to analyze data and generate predictions in industries including banking, healthcare, and marketing. The fact that classical machine learning is well-established and has a substantial body of research and tools at its disposal is one of its key advantages. Scikit-learn, TensorFlow, and PyTorch are just a few of the tools and frameworks that are available for building and training machine learning models. Furthermore, a variety of users can easily access classical machine learning models because they can frequently be trained on common computer hardware like CPUs and GPUs. However, some sorts of issues, such as those with high-dimensional data or complicated patterns, might be challenging for conventional machine learning techniques. They may not be able to handle very large datasets or complicated models due to the computational resources that are available. Quantum machine learning may be superior to classical machine learning in these circumstances [6].

2.2. Quantum Machine learning

QML is a rapidly growing area that cartels quantum computing and ML to advance novel standards and models that might have taken benefit of the exclusive principles of quantum mechanics. In quantum machine learning, data is represented using quantum bits, or qubits, which may consider any one of 0 and 1 simultaneously, allowing for much more efficient and powerful computations. There are several types of QML standards, including quantum variational algorithms, quantum-based neural networks (QNN), and quantum support vector machines [8]. These algorithms control the properties of quantum mechanics, such as entanglement and superposition, to make calculations that are not possible with classical computing. By using these principles, we can efficiently perform key distribution over multiple parties to provide confidentially to their sensitive data in the form of images, audio, video, etc. [7]. The main benefit of QML is the probability of exponential quickening in a few applications, such as optimization and data analytics. QML algorithms can also potentially handle high-dimensional data and complex patterns more efficiently than classical machine learning algorithms. However, there are also several challenges to quantum machine learning, including the issue of noise and error correction, the limited amount of qubits currently available in quantum computers, and the difficulty of developing and optimizing quantum machine learning algorithms. As a result, QML is tranquil in its initial phases of growth and needs more exploration to realize its capability fully [9]. Overall, quantum machine learning represents an exciting new area of research and has the capacity to transform numerous domains, such as drug discovery, materials science, and cryptography, among others [10] [16][18][25]27].

2.3. Convolutional Neural Network (CNN)

The classical CNN i.e., Convolutional Neural Network is used as the basic algorithm to process the data in the classical machine learning technique. The processing of images and videos frequently makes use of a form of neural network called a convolutional neural network (CNN). It is intended to acquire and excerpt pertinent structures from input images automatically, then use those features to infer predictions about the substance of the input image [11].

2.4. Quantum Neural Network (QNN)

A Quantum Neural Network (QNN) is a kind of network that is intended to track a quantum device. It uses quantum properties like entanglement and superposition to conduct various procedures on data. QNNs are composed of quantum gates, which are analogous to the layers in classical neural networks. The gates perform operations on qubits, which are the quantum equivalent of bits in classical computing. The gates can be used to perform quantum algorithms that can solve problems that are difficult or impossible to solve with classical computers [5][10] [12-13] [20-23].

2.5. Binary Image Classification

Binary image classification is a specific chore in computer vision that involves categorizing an image into one of two classes. This is typically achieved by training a machine learning model on a labeled dataset of images, where each image is associated with a label indicating its class. The model aims to learn a decision boundary that splits the two modules in feature space so that it can accurately classify new, unseen images. Binary image categorization is possible using a variety of ML techniques, like decision trees, logistic regression, random forests, and CNN [19]. The algorithm selected will depend on the specific problem at hand as well as the size and complexity of the dataset [1].

3. Existing models

There are some existing models that are proposed as opponents of classical machine learning technology. The main reason to create models that can outperform the classical techniques the speed and large running time for processing. Although the existing quantum models have issues with the noise and the error corrections. Quantum systems are inherently noisy and prone to errors thus it can be difficult to maintain the coherence of the qubits over a long period of time. The existing models also face the issue of handling a large amount of data as there is an issue with handling the qubits for a long period of time. The existing quantum models can outperform the classical machine learning models but the classical ML models can be more accurate comparatively as the quantum technology is still emerging and prone to errors. Some existing quantum models that are capable of high processing capacity than the TML mechanisms are listed below [12-14]:

3.1. Quantum Support vector machines (QSVM)

The quantum version of the classical system-based support vector machine algorithm (SVM), known as quantum-based support vector machines (QSVM), is thought to be radically quicker than the traditional standard for some kinds of problems, such as binary classification of large, high-dimensional datasets [7][27].

3.2. Quantum Principal Component Analysis (QPCA)

This is a quantum version of the traditional principal component analysis algorithm that is believed to provide a radical quickening for a few types of problems, like dimensionality reduction of high-dimensional datasets [8][28].

3.3. Quantum K-Means clustering

This is a quantum version of the classical k-means clustering standard that is believed to offer a radical quickening for certain types of problems, such as clustering large, high-dimensional datasets [14]. These quantum machine learning models hold great potential for resolving some of the most difficult issues in artificial intelligence and data science, even though they are even in the initial phases of progress and have not yet been demonstrated to perform well as compared to the TML in actual use. [25]

4. Model and Design Goals

The method we are proposing is a comparison between the classical machine learning techniques and the quantum machine learning techniques. The QML techniques can process a larger amount of data than compared to the TML mechanisms. In this project, we have run the algorithms on the FASHION MNIST dataset with the CNN and the QNN. The CNN is run as the classical machine learning algorithm and the QNN is run as the quantum machine learning algorithm. [10][18] [22-23]

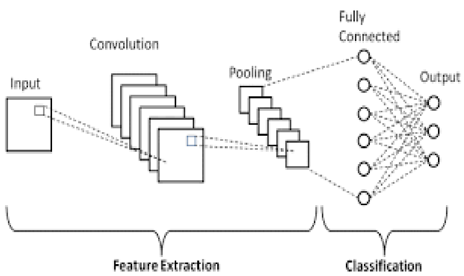

Fig.1 CNN Overview

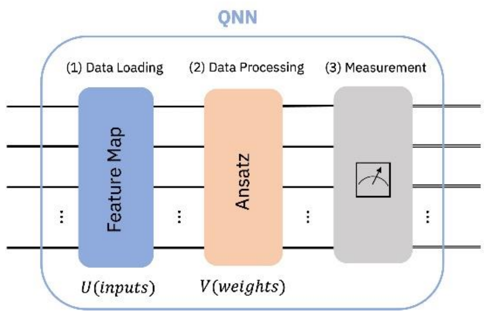

Fig.2 QNN Overview

4.1. TML vs QML

TML techniques are based on classical computers and use classical algorithms to process data and make predictions. These techniques are widely used in various fields, such as finance, healthcare, and marketing [3][12-13]. On the other hand, quantum machine learning (QML) techniques are based on quantum computers and use quantum algorithms to process data and make predictions. Quantum devices use qubits, which may endure in several states at once, to implement calculations. QML is a rapidly developing area that has the capability to transform various fields. One of the key advantages of QML over classical ML is its facility to complete a few calculations much quicker than traditional devices. For example, quantum computers can quickly address a few optimization problems that would take traditional computers an impractically long time to solve. This means that QML has the promise to enhance the speed and adeptness of various computational tasks. However, QML is even in its initial phases and quantum devices are still relatively unstable and error-prone. This means that QML algorithms are currently limited in their complexity and the size of data sets that they can handle. In addition, quantum computers are expensive to build and maintain, which limits their accessibility. In summary, classical ML techniques are currently more widely used and accessible than QML techniques, but QML has the capability to transform several fields by improving the speed and efficiency of certain computational tasks. [3] [12-13]

5. Issues that can be optimized by QML

There are some issues that may be optimized with the help of QML techniques. The TML techniques are more accurate compared to the quantum machine learning methods but the speed and processing time can be minimized by using the quantum machine learning techniques. The quantum methods take minimal time and have the capability of processing the data with higher speed rates comparatively. The issues faced by the classical machine learning can be optimized by the QML are listed below:

5.1. Optimization

QML is much quicker than conventional computers at solving optimization issues. This is due to the fact that quantum parallelism, which allows for the simultaneous exploration of numerous potential solutions, allows for exponential speedups for some issues.

5.2. Pattern Recognition

Classifying and identifying trends in data can be done much more quickly with QML than with traditional algorithms. For instance, pattern recognition jobs can be more effectively completed by quantum models like the QSVM and QKNN. [5-6]

5.3. Simulation

QML can be used to simulate complex physical systems that are complicated to simulate using traditional systems. For instance, QML algorithms can be employed to simulate the behavior of molecules and chemical reactions, which can have important applications in drug discovery and materials science [15].

5.4. Machine Learning Encrypted Data

QML can be used to perform machine learning on encrypted data without decrypting it, which can improve the privacy and security of sensitive data [6] [11][19].

5.5. Natural Language Processing (NLP)

QML can potentially improve the speed and accuracy of NLP activities like language translation and sentimental analysis.

6. Problems Identified

The problems identified while using the classical machine learning algorithms for binary image classification are mentioned in this paragraph. One problem that can arise when using classical machine learning (ML) algorithms for binary image classification is the difficulty in accurately detecting and classifying objects that have high variability in shape or appearance. This is often referred to as the "intra-class variability" problem. For example, if you were training a classifier to distinguish between images of cats and dogs, the classifier might have difficulty distinguishing between different breeds of cats or dogs, or between images taken in different lighting conditions or from different angles. Another problem that can arise is the problem of overfitting. Overfitting occurs when the standard is too complicated and memorizes the exercising data rather than generalizing it to the latest data. This can lead to inadequate functioning of the latest data and a lack of generalizability. In addition, classical ML algorithms can be computationally expensive and require large amounts of training data to achieve high accuracy, which can be a challenge when working with high-dimensional image data. QML techniques have the capacity to address some of these challenges by leveraging the power of quantum machines to investigate several potential solutions instantaneously and capture the complexity and variability in image data more efficiently. However, the area of QML is even in its initial phases, and extensive exploration is required to determine the most effective approaches for binary image classification. [3][10] [12-13]

The problems that are faced while processing the binary image classification in the classical machine learning methods are stated below:

Overfitting in the image data

Variability in the image data

Background noise in the image data

Limited amount of data acquisition

Human error in the annotation

7. Optimization through QML Model

The issues faced by the existing models and the TML methods can be optimized by the QML methods. The quantum machine learning method can minimize the processing time and produce optimized results comparatively. The issues identified such as overfitting in the image data, variability in the image data, background noise in the image data, a limited amount of data, and human error in the annotation can be optimized by using the quantum machine learning method as:

7.1. Quantum Feature Maps

Quantum feature maps can be used to map the initially entered image info to a high-dimensional feature space, where the underlying correlations among the characteristics and the destinated variable are easier to model. By using a quantum circuit to alter the input image data into a higher-dimensional feature space, the model can potentially capture more of the signal and reduce the impact of background noise [17].

7.2. Quantum Denoising Algorithms

By performing calculations on the incoming data using quantum circuits, quantum denoising algorithms can be used to remove noise from image data. These algorithms have the ability to be more effective and produce better results than traditional denoising algorithms [18].

7.3. Quantum Intuitive algorithms

Quantum-inspired conventional algorithms, such as quantum-inspired neural networks or quantum-inspired clustering algorithms, can be used to capture the complexity and variability in image data while minimizing the impact of background noise [19].

7.4. Quantum Data Augmentation

Quantum data augmentation can be used to theatrically improve the diversity and size of the training data set by employing arbitrary alterations to the input images, such as adding noise or blurring. By using quantum circuits to apply these transformations, the model can potentially learn to recognize objects even in the presence of background noise [20].

8. Objectives

Optimizing the overfitting in the image data: Overfitting occurs in machine learning when a standard is too difficult and measures the training data too intimately, leading to inadequate generalization to new data. This can be a problem in image data, where there may be a large number of features and high dimensionality, making it difficult to accurately model the underlying relationships among the characteristics and the destinated variable.

Variability in the image data: Image data can have variability due to factors such as lighting conditions, occlusions, and variations in object position or orientation. This can make it difficult for classical machine learning (ML) algorithms to accurately classify images.

Optimizing the background noise: Background noise in image data can be a challenging trouble for ML algorithms, as it may interfere with the accurate detection of features and objects in the image. QML techniques have the capability to address the problem of background noise in image data by leveraging the ability of quantum computers to perform parallel computations and explore many possible solutions simultaneously [21-22].

9. Implementation

The method we are proposing is a comparison between the TML techniques and the QML techniques. The QML techniques are capable of processing a larger amount of data than compared to the TML approaches. In this project, we have run the algorithms on the FASHION MNIST dataset with the CNN and the QNN. The CNN is run as the classical machine learning algorithm and the QNN is run as the QML algorithm.

Data Preparation: The dataset considered is the mostly used FASHION MNIST dataset. The Fashion MNIST dataset is a gathering of clothing-related grayscale images that are frequently used in image classification tasks in machine learning studies. It has evolved into a well-liked benchmark for assessing new machine-learning algorithms and is frequently treated as an alternative to the fundamental MNIST dataset, which entails handwritten numbers. Each of the 70,000 images in the Fashion MNIST collection is a 28x28 pixel grayscale image of a piece of clothing. T-shirts, sneakers, pants, dresses, pullovers, coats, sandals, shirts, bags, and ankle boots are just a few of the ten various categories of clothing that exist. The dataset is split into a training set of 60k pictures and a test set of 10k pics, and every image is labeled with the appropriate category. [4].

Classical CNN: The classical CNN is used as the basic algorithm to process the data in the classical machine learning technique. The processing of images and videos frequently makes use of a form of neural network called a convolutional neural network (CNN). It is intended to acquire and obtain pertinent features from input images automatically, then use those features to infer predictions about the substance of the input image.

Quantum Circuit preparation: In this methodology the quantum neural network used processes the data by using the 'Qubits' and circuits that are said to be Quantum circuits. The quantum circuits are then used to classify the data. Collections of quantum gates are linked by quantum wires to form quantum circuits. The unitary transformation U, which is passed by the circuit determines the precise configuration of a quantum circuit, the counter, and kinds of gates, as well as the interconnectedness design. A crucial part of quantum computing and quantum information handling are quantum circuits. They are comparable to conventional digital circuitry, but instead of conventional bits, they use quantum bits, also known as qubits. [1-3][12-13] A series of quantum gates, or actions that affect one or more qubits, make up a quantum circuit. These gates can generate and control entangled states and carry out a number of operations, including rotations, flips, and swaps.

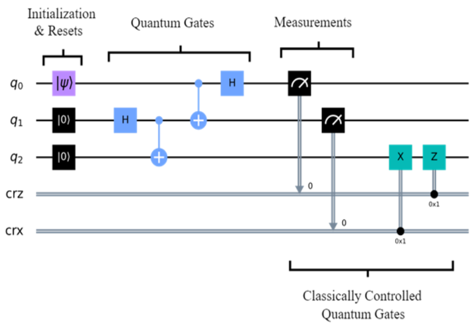

Fig.3 Quantum circuit

Quantum Model preparation: A ML model that employs quantum processing is referred to as a "quantum model." Quantum models, as opposed to conventional machine learning models, work with quantum bits, or qubits, and can take benefit of the special features of quantum mechines to carry out some tasks more effectively. [2-3] [12-13].

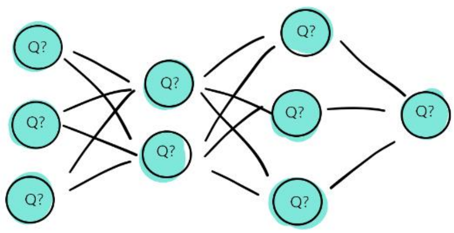

Fig.4 Quantum Network

Quantum training ; quantum training is the method of using quantumn computing to train a quantum machine learning model. A crucial component of QML is quantum training.

Quantum training: Quantum training is the method of using quantum computing to train a quantum machine learning model. A crucial component of QML is quantum training, which enables the creation of novel machine learning models and algorithms that benefit from the special properties of quantum mechanics. Quantum training can be done using a variety of methods, such as quantum transfer learning, quantum reinforcement learning, and quantum variational algorithms. These methods use various strategies and algorithms, but they all aim to use quantum computing to optimize the parameters of a quantum machine learning model. [3][4]

Model Evaluation: The model evaluation is done after the test data and train data are filtered and are ready to process the further algorithms. In the quantum machine learning mechanism, the test data and the train data are converted to binary form as the quantum algorithms may not process a substantial amount of data. The feature extraction is processed on the binary data and the quantum circuits using the specific libraries are employed. In the QML mechanism, the TensorFlow-quantum and the Cirq frameworks are used to process the data. When it comes to the TML mechanism is processed on the FASHION MNIST dataset using the Convolutional Neural Network algorithm. After processing the data using both specified models the optimization is checked. Although quantum machine learning is still an emerging technology it can process the data faster than the classical machine learning mechanisms but the QML is still prone to many errors and noise compared to the classical machine learning techniques. [2][3]

10. Results and Discussions

The proposed model is a comparison between the TML techniques and the QML techniques. The classical CNN is used for TML and the QNN is used for the QML. The accuracy rates obtained are mentioned below. The below visualizations are the image data before converting into the binary level and after converting it into the binary level for further processing. The results obtained after the implementation of the QNN algorithm [23][25][27][28]:

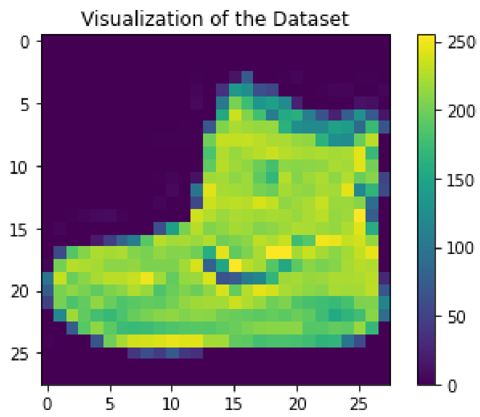

Fig.5 Before downscaling the image data

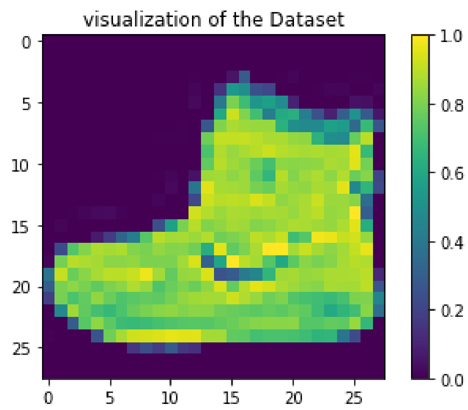

Fig.6 After downscaling the image data

The image data from the dataset has to be reshaped and resized as the flow of the qubits in the quantum circuit has to be controlled. If the pixels of the data taken are less than the flow of large qubits can be handled. For this we have to resize the images. The visualization after resizing the image data is shown in the Fig.7.

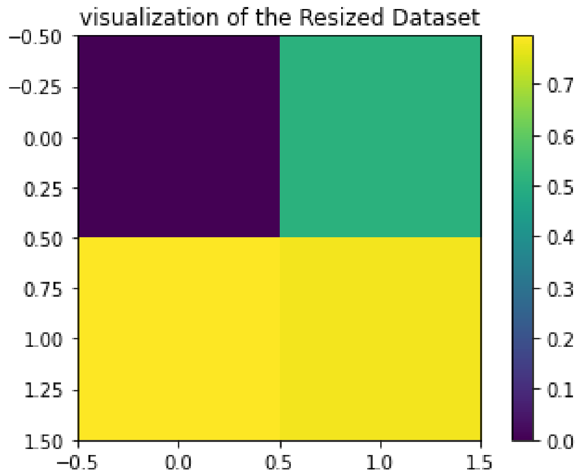

Fig.7 Visualization after reshaping the image data

The quantum circuit produced is the evaluation and controlling the qubits in order to produce the desirable results. The quantum circuit produced after performing the binary image classification on the FASHION MNIST dataset is displayed in the Fig.8.

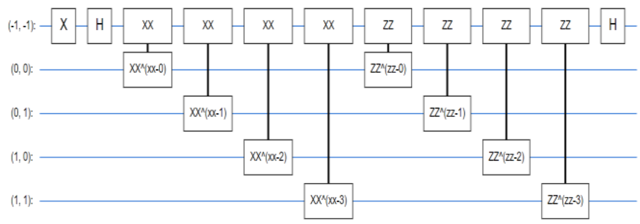

Fig.8 Quantum circuit generated.

By utilizing the quantum computer's capacity for parallel calculations and simultaneous exploration of numerous alternative solutions QML techniques offer the potential to address the issue of background noise in image data. The accuracy of the quantum circuit is measured using the Hinge accuracy and Hinge loss. The optimizer used is Adam. The accuracy scale measures are visualized in the below Fig.9 and Fig10.

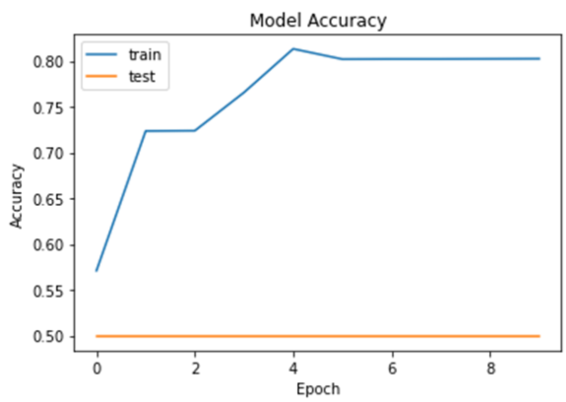

Fig.9 Accuracy

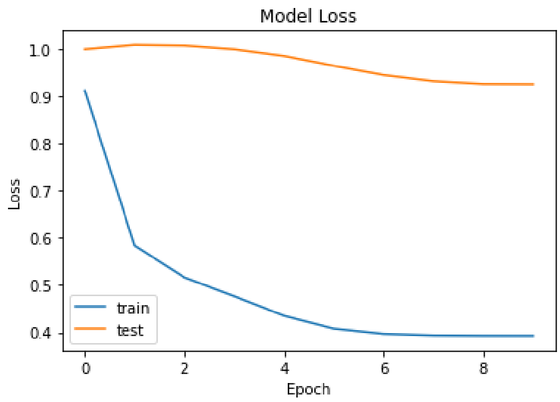

Fig.10 Loss

11. Conclusion and Future Scope

Conclusion

This method is performed to check the speed variations of the TML and the QML algorithms. The QML algorithm QNN has a faster processing capacity than compared to the classical CNN. CNN can transmit a large amount of data with minimal loss as QNN is still an emerging technology. when the QNN is processing the data the loss of accuracy is higher than the CNN. CNN has shown the minimal loss. although the QNN can perform the processing with minimal time and comes in handy when the data is to be processed in high-speed rates.

Future Scope

The QNN is still an emerging technology and has issues with errors and large data handling. Despite of these issues the QNN can process the data at faster rates than compared to the classical machine learning techniques. There are two distinct methods of machine learning, known as QNNs and CNNs, which are founded on various computational paradigms. While QNNs are a relatively new field and are still being researched, CNNs have been thoroughly studied and have produced remarkable results in a variety of fields. Overall, QNNs and CNNs each have their own advantages and disadvantages, and it is probable that the future of machine learning will combine both techniques. To completely comprehend QNNs' capabilities and constraints, much more research needs to be done. Their potential is still being explored. By the improved hardware, some algorithmic improvements, hybrid approaches and building quantum inspired classical models the QNN can be the next ruling technology with high-speed computing capabilities. The quantum technologies can be also improved in many cases in the coming ages. As the world is going behind the smartness the quantum approaches can be used to enhance the IIOT devices and the IoT devices for the faster performance in the desired area [21]. It can also be used in the cloud storage and accessing systems to make more secure and independent of many networks to optimize the performance [9][15][19][24][26].

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