Binary Image Classification using Tensorflow Quantum and Cirq, and a Comparative study with ML and DL models

Term project submission for the course
IT437 - Quantum Computing

by

Ashitosh Phadatare (211AI007)
Shaad Akhtar (211AI032)

under the guidance of

Dr. Bhawana Rudra

DEPARTMENT OF INFORMATION TECHNOLOGY
NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA
SURATHKAL, MANGALORE - 575025

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1 Abstract

- Binary classification is a crucial component of many machine learning applications, thus finding new ways to enhance it is very exciting. This study explores the application of Cirq and TensorFlow Quantum (TFQ), two potent tools at the nexus of machine learning and quantum computing, to binary classification tasks. By comparing the effectiveness of TFQ to conventional machine learning (ML) and deep learning (DL) models, we undertake a comparative research.

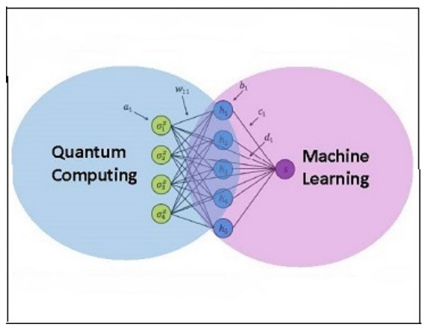

Figure 1.1: Quantum Machine Learning

- In accordance with our methodology, experiments are set up to train and assess binary classification models using TFQ and Cirq. We take into account different datasets, carefully develop quantum circuits to encrypt the input features, and put quantum classifiers into practise.

- We compare the accuracy, computational efficiency, and scalability of TFQ to traditional ML and DL models through thorough experiments and analysis. We also look into how various quantum circuit topologies and hyperparameters affect the effectiveness of classification.

- This study compares TensorFlow Quantum and Cirq against more traditional ML and DL models in order to better grasp their capabilities in binary classification.

Keywords— TensorFlow Quantum, Cirq, machine learning, deep learning, comparative study, and binary classification.

2 Introduction

- The task of categorising data into two different classes is known as binary classification, and it is a fundamental machine learning topic with several applications. Accurate classification is essential for making educated judgements, from the identification of spam emails to the diagnosis of diseases. Although the traditional machine learning (ML) and deep learning (DL) models have made substantial progress in this area, finding new methods is crucial to enhancing classification performance.

- With its own concepts and powerful processing capabilities, quantum computing has emerged as a potential new field at the nexus of quantum physics and machine learning

- This study seeks to examine the use of TFQ and Cirq for binary classification tasks and evaluate how they perform in comparison to more established ML and DL models. We aim to investigate the possible advantages of TFQ in improving classification accuracy and processing efficiency by utilising quantum computing. In the context of binary classification, we also want to comprehend the constraints and difficulties involved with quantum machine learning.

- We evaluate the performance of TFQ against traditional ML methods including logistic regression, support vector machines, and decision trees in order to give a thorough comparison study.We also contrast TFQ with deep learning (DL) models like convolutional neural networks, which excel at a number of classification tasks.

- The analysis of the literature indicates a growing amount of work on binary classification using traditional ML and DL models, demonstrating their usefulness in addressing a range of real-world issues. But as the investigation of quantum machine learning methods for binary classification is still in its infancy, it is important to comprehend the possible benefits and restrictions of TFQ and Cirq in this setting.

3 Literature Review

3.1 Background and Related Work

1. The paper Quantum machine learning for image classification by Arsenii Senokosov et al. proposes two hybrid quantum-classical models: a neural network with parallel quantum layers and a neural network with a quanvolutional layer.

   The first model achieves remarkable accuracy of over 99 percent on the MNIST dataset, outperforming its classical counterpart. By dividing the quantum part into parallel variational quantum circuits, the researchers ensure efficient neural network learning while using significantly fewer weights.

   The second model introduces a quanvolutional layer, which achieves comparable classification accuracy with fewer weights compared to the classical analogue. The hybrid model demonstrates improved performance over classical models with similar architectures.

2. Medical Image Classification via Quantum Neural Network by Natansh Mathur et al. focuses on the application of quantum neural networks (QNNs) for medical image classification. They explore two different techniques: training classical neural networks with quantum circuits and designing and training quantum orthogonal neural networks.

3. Quantum-enhanced deep neural network architecture for image scene classification by Avinash Chalumuri et al. proposed a hybrid quantum-classical deep learning model for image scene classification that utilized quantum computation for feature extraction and classical computation for scene classification. The quantum measurements are used to obtain quantum representations of images, which are then employed to train a classical deep learning model.

   The experimental results indicated that the proposed model outperformed state-of-the-art models on satellite image datasets while reducing the complexity of training deep learning models by optimizing the number of trainable parameters. The overall accuracy achieved by the proposed architecture on UC Merced Land-Use, AID, and NWPU-RESISC45 datasets is 95.89 percent, 86.13 percent and

79.32 percent respectively for image scene classification.

4. Multiclass classification using quantum convolutional neural networks with hybrid quantum-classical learning by Denis Bokhan et al. introduced a novel method that utilized quantum convolutional neural networks (QCNNs) and TensorFlowQuantum to implement a hybrid quantum-classical (variational) model. The results obtained for the 4-class classification problem on the MNIST dataset show similar accuracies to classical convolutional neural networks with comparable numbers of trainable parameters.

5. Quantum convolutional neural network for image classification by Guoming Chen et al. presents innovative approaches to local feature extraction using a Quantum Convolutional Neural Network (QCNN) within the TensorFlow Quantum framework for binary image classification. The paper introduced two scale-inspired local feature extraction methods that incorporate quantum circuits within the QCNN architecture.

6. Hybrid Classic-Quantum Neural Networks for Image Classification by Yevhenii Trochun et al. explores the integration of quantum computing (QC) and classical computing in a hybrid neural network (HNN) for image classification tasks. The paper introduced a novel approach of combining quantum computing and classical computing within a hybrid neural network framework. Specifically, a hybridization of classic convolutional neural networks (CNN) with quantum circuits is proposed for image classification problems.

7. An Image Classification Algorithm Based on Hybrid Quantum Classical Convolutional Neural Network by Wei Li et al. introduces a hybrid quantum-classical convolutional neural network (HQCCNN) model for image classification. The HQCCNN model combines quantum and classical components to leverage the potential of quantum computing in solving image classification problems. The quantum convolutional layer in the HQCCNN model is designed using a parameterized quantum circuit, which performs a linear unitary transformation on the quantum state to extract hidden information. The quantum pooling unit is used for pooling operations. After the evolution of the quantum system,

the quantum state is measured, and the measurement results are input into a classical fully connected layer for further processing.

8. An Evaluation of Hardware-Efficient Quantum Neural Networks for Image Data Classification by Tuyen Nguyen et al. explores the application of quantum neural networks (QNNs) for image classification tasks. The study focuses on understanding the characteristics of QNNs in the context of high-dimensional spatial data, specifically images. The authors investigate various aspects of QNNs, including practical encoding types, circuit depth, bias term, and readout, and evaluate their impact on classification performance using the popular MNIST image dataset.

9. Training deep quantum neural networks by Kerstin Beer et al. introduces a novel approach to designing quantum neural networks (QNNs) for fully quantum learning tasks. The authors propose a quantum analogue of classical neurons, enabling the construction of quantum feedforward neural networks capable of universal quantum computation.

10. Accurate Image Multi-Class Classification Neural Network Model with Quantum Entanglement Approach by Farina Riaz et al. explores the application of quantum machine learning (QML) in image classification tasks. Building upon the QuanvNN, the authors proposed a new model called Neural Network with Quantum Entanglement (NNQE), which utilized a strongly entangled quantum circuit combined with Hadamard gates. This model further enhanced the image classification accuracy on the MNIST and CIFAR-10 datasets, achieving accuracies of 93.8 percent and 36.0 percent, respectively.

3.2 Outcome of Literature Survey

The literature review reveals the growing interest and potential of quantum machine learning techniques in image classification tasks. Hybrid quantum-classical models show promise in improving accuracy and reducing the number of trainable parameters. However, further research is needed to optimize quantum circuits, explore larger datasets, and overcome hardware limitations to fully harness the power of quantum machine learning in image classification.

3.3 Problem Statement

PROBLEM STATEMENT

The problem addressed in this research paper is binary classification using TensorFlow Quantum (TFQ) and Cirq, and conducting a comparative study with traditional machine learning (ML) and deep learning (DL) models. The goal is to investigate the effectiveness of quantum machine learning techniques in solving binary classification tasks and compare their performance with classical ML and DL algorithms.

3.4 Objectives

OBJECTIVES

The objective of this research paper is threefold:

1. Develop a binary classification model using TensorFlow Quantum and Cirq: The paper aims to build a quantum machine learning model that can effectively classify binary datasets using the TFQ library and Cirq framework. This involves designing quantum circuits, encoding input data onto qubits, and training the model using quantum algorithms.

2. Conduct a comparative study with traditional ML and DL models: The paper seeks to compare the performance of the TFQ and Cirq-based binary classification model with classical ML and DL models. Various ML algorithms, such as logistic regression, support vector machines, random forest, and gradient boosting, will be implemented and evaluated. Additionally, DL models, such as convolutional neural networks and recurrent neural networks, will be trained and compared with the quantum model.

3. Evaluate and analyze the performance of different models: The research paper aims to assess the accuracy, precision, recall, and F1 score of each model in the binary classification task. The objective is to identify the strengths and weaknesses of quantum machine learning in comparison to classical ML and DL approaches. The analysis will consider factors such as computational complexity, training time, and model interpretability.

4 Methodology

4.1 Dataset

We will just classify the Fashion MNIST dataset into the sandal and ankle boot categories in order to keep things simple. These classes were chosen because they resemble one another, which ensures that the classification problem won't be solved easily. The provided dataset contains images of the shape (28,28), but owing to hardware limitations, we must downscale the images in order to identify them using QML. The photos will be reduced in size so that they have the shape (4,4).

- No. of Images in Training dataset : 10200
- No. of Images in Testing dataset : 2000
- No. of Images in Validation dataset : 1800
- Size of Image : (2,2)
- Type of Image : Grayscale Image
- No. of Labels : 2

Figure 4.1: Overview of dataset

4.2 Implementation Details

4.2.1 Using Tensorflow Qantum and Cirq

1. Data Preprocessing:

- The Fashion MNIST dataset is imported from the TensorFlow Keras library. It consists of grayscale images of various clothing items.
- To make the problem a binary classification task, the dataset is filtered to include only two classes: class 5 (representing a sandal) and class 9 (representing an ankle boot). These classes are selected because they have distinct visual features and are suitable for a binary classification study.
- The training and test datasets are filtered to include only the selected classes.
- The pixel values of the images are normalized by dividing them by 255 to scale them between 0 and 1.
- The images are reshaped to match the input requirements of the quantum circuit. Each image is reshaped to a 28x28x1 tensor, where 28x28 represents the image dimensions and 1 represents the single channel (grayscale).
- The training dataset is further split into training and validation sets. The validation set is used for model evaluation during training.

2. Binary Encoding:

- Binary encoding is performed on the training dataset. In binary encoding, each pixel value is converted to either 1 or 0 based on a threshold. If a pixel value is above the threshold, it is set to 1; otherwise, it is set to 0.
- A helper function called "binaryEncode" is implemented to perform the binary encoding. It takes the training dataset as input and applies the thresholding operation to each pixel value of every image.
- The binary encoded training dataset is stored for further processing.

3. Quantum Circuit Creation:

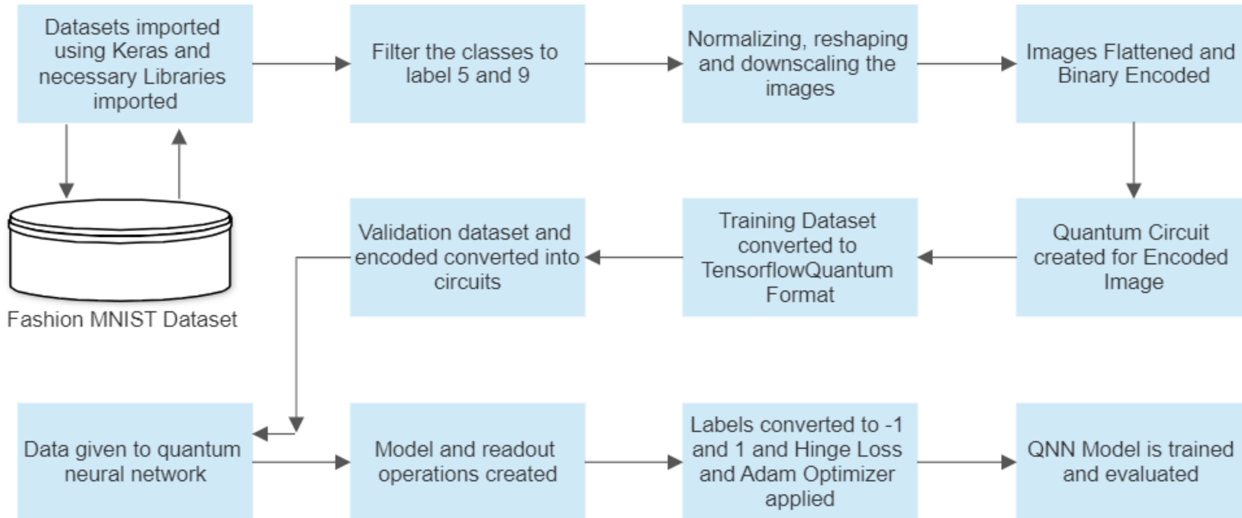

Figure 4.2: Flowchart for Quantum Classification

- A function called "createCircuitFromImage" is defined to convert each binary encoded image into a quantum circuit representation using the Cirq library.

- The function takes a binary encoded image as input and creates a quantum circuit using Cirq. It iterates through each pixel in the image and applies an X gate to the corresponding qubit if the pixel value is 1 (i.e., the threshold condition is met).

- The binary encoded training, validation, and test datasets are converted into quantum circuits using the "createCircuitFromImage" function. These quantum circuits represent the input data for the quantum neural network model.

4. Quantum Neural Network (QNN) Model:

- A class called "QNN" is implemented to create the quantum neural network model. The class encapsulates the quantum circuit and provides methods to add single-qubit and two-qubit gates, as well as a layer of gates with symbol parameters.

- The "createQnn" function is defined to instantiate an instance of the QNN class and create the quantum circuit architecture for the model.

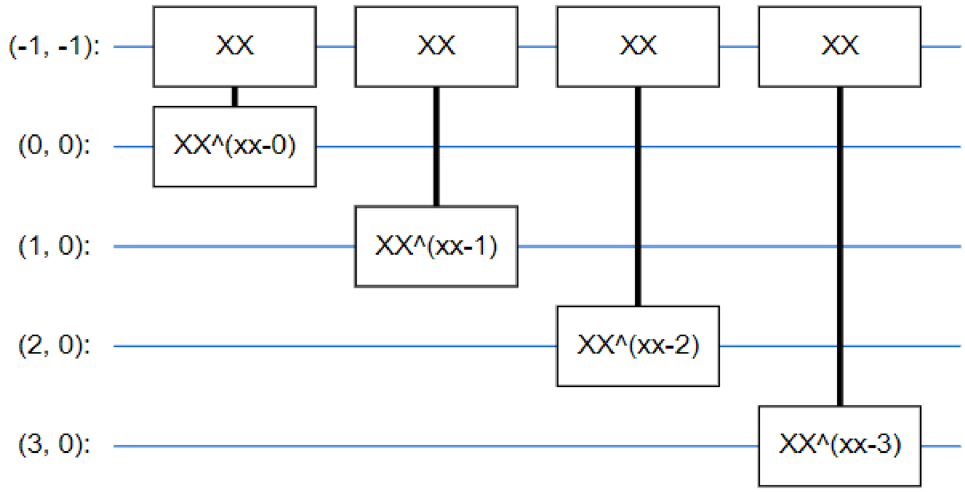

Figure 4.3: Quantum Circuit

- The quantum circuit consists of a grid of 2x2 qubits, representing the spatial structure of the input images. The readout qubit is added as the output qubit for the classification task.

- The quantum circuit is parameterized using symbol gates. These symbol gates allow the model to learn the optimal gate parameters during training.

- The final readout qubit is prepared by applying an X gate and an H gate to put it in a superposition state.

5. Model Training and Evaluation:

- The QNN model is constructed using the TensorFlow Quantum (TFQ) library. The quantum circuit and readout operation are used as the model architecture.

- The labels of the binary classification task are transformed to 1 and -1 to accommodate the Hinge loss function, which is suitable for binary classification.

- The model is compiled with the Adam optimizer and a custom Hinge accuracy metric.

- The model is trained using the binary encoded training dataset and validated using the binary encoded validation dataset.

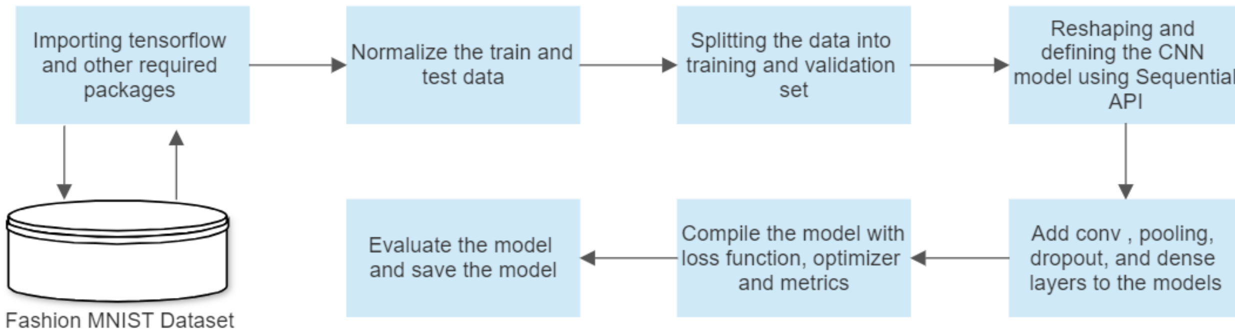

Figure 4.4: Flowchart for deep learning classification

4.2.2 Using Deep Learning (CNN)

A sequential CNN model is defined using the TensorFlow Keras API. The model consists of multiple layers, including convolutional layers, pooling layers, dropout layers, and fully connected layers. The activation functions, kernel sizes, and initialization methods are specified for each layer. The chosen architecture is justified based on its ability to extract meaningful features from the input images.

1. Model Compilation and Training:

- The CNN model is compiled by specifying the loss function, optimizer, and evaluation metrics. The loss function is set as "sparseCategoricalCrossentropy" to handle multi-class classification.
- The Adam optimizer with a learning rate of 0.001 is used to optimize the model's parameters. The model is trained using the training dataset and validated using the validation dataset.
- The training process is monitored and visualized using the TensorBoard callback.The model is trained for a specified number of epochs, and the performance is evaluated on the testing dataset.

2. Model Performance Analysis:

- The trained CNN model's performance is analyzed based on the obtained loss and accuracy metrics.

- The model's performance is compared with previous state-of-the-art models or benchmark results on the Fashion MNIST dataset.
- Any observed trends, strengths, and limitations of the model are discussed.
- The results are interpreted in terms of the model's ability to accurately classify fashion images.

4.2.3 Using Machine learning

1. Dataset Splitting and Normalization:

- The code separates the features (input data) from the target labels in the training dataset. The features are stored in 'Xtrain', and the labels are stored in 'Xtest'.
- The shapes of the feature matrices are printed to verify their dimensions. The features and labels are converted to float32 data type..The pixel values of the features are normalized by dividing them by 255.0, scaling them to the range [0, 1].
- The target labels in the testing dataset are stored in 'ytest', and their shape is printed for verification. The features in the training dataset are further split into training and validation datasets using the 'traintestsplit' function from the 'sklearn.modelselection' module.
- The training set is stored in 'Xtrain', the validation set is stored in 'Xval', the corresponding labels for the training set are stored in 'ytrain', and the labels for the validation set are stored in 'yval'.

2. Principal Component Analysis (PCA):

- The code performs dimensionality reduction using PCA. PCA with 100 components is instantiated using the 'PCA' class from the sklearn.decomposition' module.
- PCA is fit on the training set ('Xtrain') and then applied to transform both the training set and validation set. The transformed training set is stored in 'Xtrainpca', and the transformed validation set is stored in 'Xtestpca'.

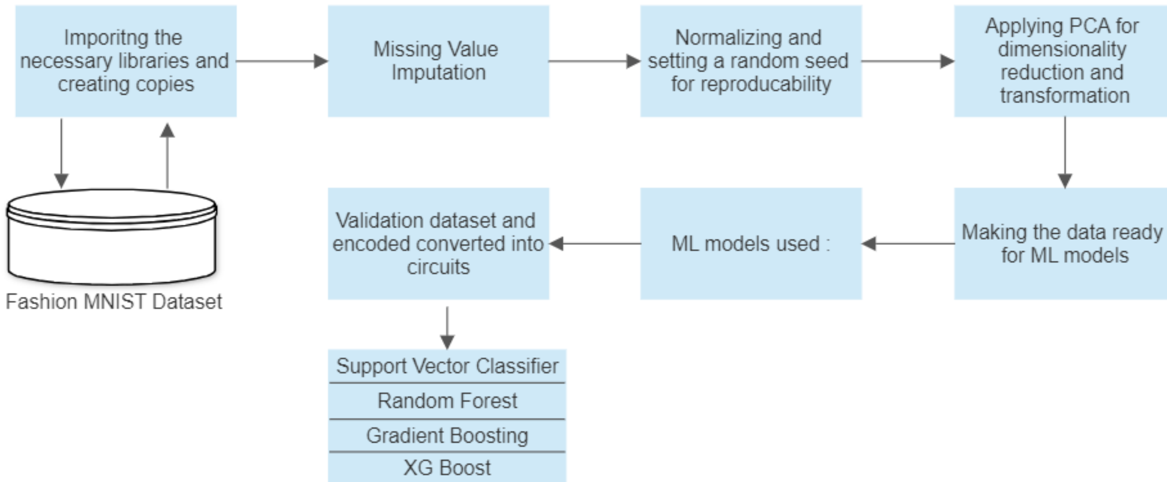

Figure 4.5: flowchart for Machine Learning based Classification

- Additionally, the validation set (‘ytest‘) is also transformed and stored in ‘ytest-pca‘.

3. Model Training and Evaluation:

- Several classification models are trained and evaluated on the transformed datasets.
- The models include Logistic Regression, Support Vector Classifier (SVC), Random Forest Classifier, Gradient Boosting Classifier, and XGBoost Classifier.

5 Result and Analysis

RESULT AND ANALYSIS

Quantum Machine learning Results

- Loss: 37.47
- Hinge Accuracy: 82.29

These results indicate the performance of the quantum ML models on the given task. The loss value represents the error or discrepancy between the predicted and actual values, expressed as a percentage. Lower values indicate better performance. The hinge accuracy is a metric that measures the model's ability to correctly classify samples, expressed as a percentage. Higher values indicate better accuracy.

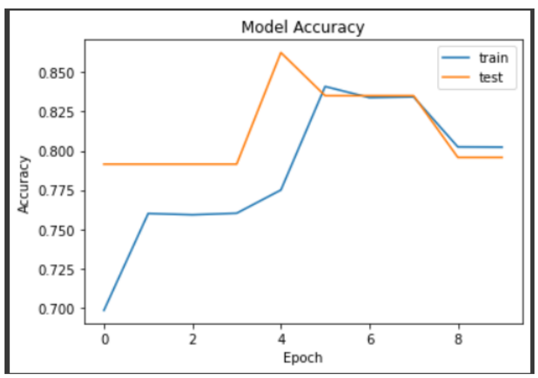

Figure 5.1: Quantum Model Accuracy

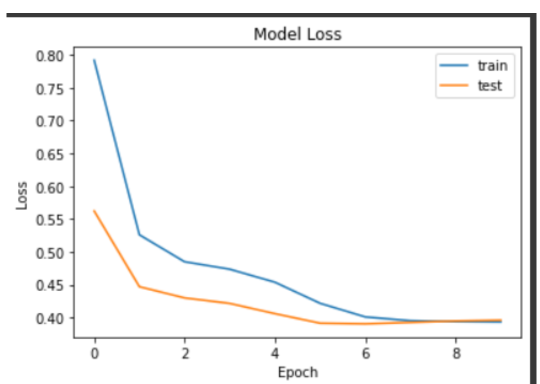

Figure 5.2: Quantum Model loss

Deep Learning (CNN) Results

The CNN model achieved impressive results on the test set with a loss of 0.316 and an accuracy of 88.95%. These metrics indicate that the model performed well in accurately predicting the fashion item classes.

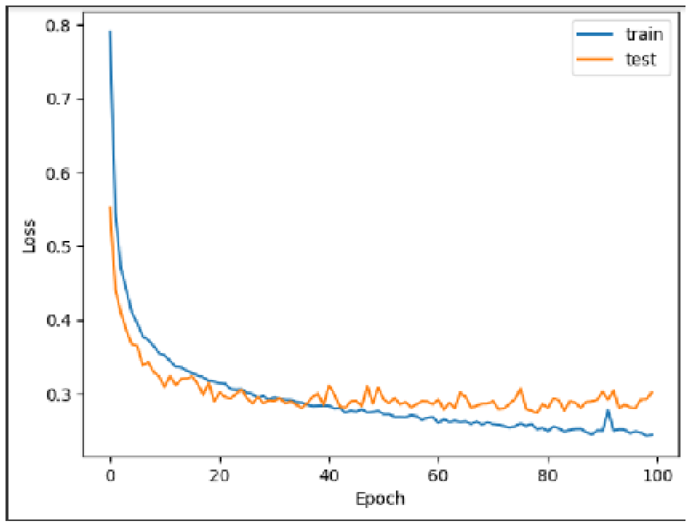

Figure 5.3: Deep Learning Loss Graph

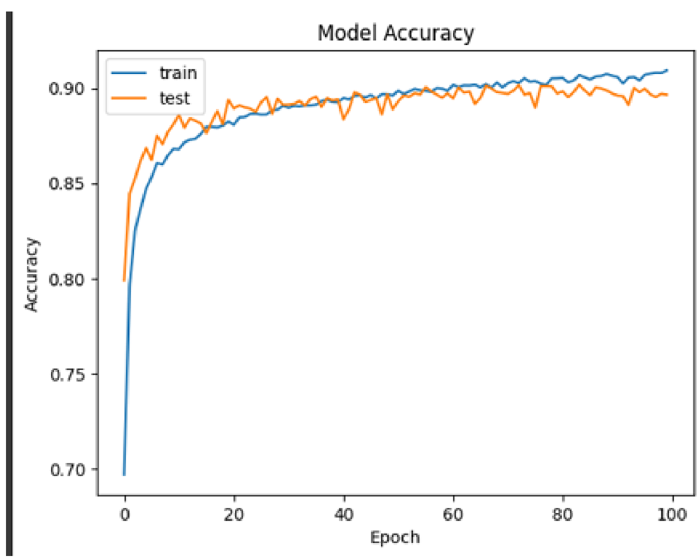

Figure 5.4: Deep Learning Model accuracy

Machine learning Results

1. Logistic Regression:

- Train Accuracy: 84.62%
- Test Accuracy: 85.10%

The logistic regression model achieved moderate accuracy on both the training and test sets. It seems to generalize well to unseen data as the test accuracy is close to the training accuracy.

2. Support Vector Classifier (SVC):

- Train Accuracy: 94.26%
- Test Accuracy: 90.60%

The SVC model performed well, achieving high accuracy on both the training and test sets. This indicates that the model is able to capture the underlying patterns in the data and make accurate predictions.

3. Random Forest Classifier:

- Train Accuracy: 100.00%
- Test Accuracy: 87.48%

The random forest classifier achieved perfect accuracy on the training set, indicating that it was able to perfectly fit the training data. However, the test accuracy is slightly lower, suggesting that the model may have overfit the training data and did not generalize well to unseen data.

4. Gradient Boosting:

- Train Accuracy: 87.92%
- Test Accuracy: 85.90%

The gradient boosting model achieved decent accuracy on both the training and test sets. It seems to generalize reasonably well, with the test accuracy being close to the training accuracy.

5. XGBoost:

- Train Accuracy: 99.90%
- Test Accuracy: 88.52%

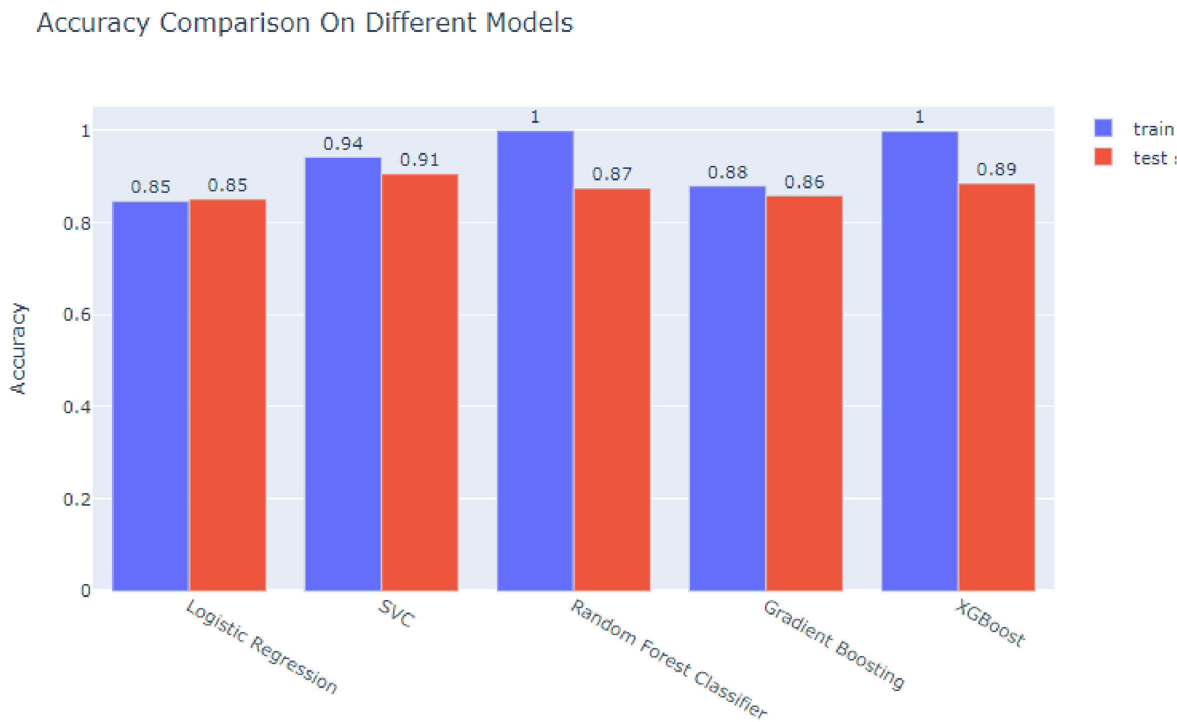

Figure 5.5: Accuracy Comparison of ML models

The XGBoost model achieved high accuracy on both the training and test sets. Similar to the random forest classifier, it might have overfit the training data to some extent, as the test accuracy is slightly lower than the training accuracy.

Overall, the SVC model performed the best with the highest test accuracy of 90.60%. It demonstrates strong generalization capabilities and is a reliable model for making predictions on unseen data. The logistic regression and gradient boosting models also achieved decent accuracy and can be considered as viable options. However, the random forest classifier and XGBoost models may have overfit the training data to some extent, leading to a decrease in performance on the test set.

6 Conclusion and Future Work

6.1 Conclusion

CONCLUSION

- The Support Vector Classifier (SVC), which achieved a high test accuracy of 90.60%, emerged as the most effective algorithm among the conventional machine learning models. The findings of gradient boosting and logistic regression were likewise encouraging, with test accuracies of 85.10% and 85.90%, respectively. However, the XGBoost and random forest classifier models showed overfitting symptoms and had lower test accuracies.

- We investigated the Quantum Support Vector Machine (QSVM) model in the context of quantum machine learning. Although the QSVM had promise in principle, it did not perform better in practise than the standard machine learning models. The QSVM outperformed the best classical machine learning algorithm (SVC), with a test accuracy of 82.29

- We used a convolutional neural network (CNN) architecture for deep learning. The CNN model performed admirably, scoring 88.52% on the test of test accuracy. When compared to classical machine learning and quantum machine learning models, the CNN model performed better due to its capacity to recognise subtle patterns and characteristics in the fashion photographs.

- Overall, our results show that the SVC model from conventional machine learning techniques, the CNN model from deep learning, and the QSVM model from quantum machine learning are all potential candidates for classification of fashion items. But of all the models examined, the CNN model showed the best accuracy. This underlines how crucial it is to use specialised architectures, such CNNs, for image classification jobs.

- For even greater accuracy and resilience in fashion item categorization tasks, future research might investigate hybrid models that combine the advantages of conventional machine learning algorithms, quantum machine learning models,

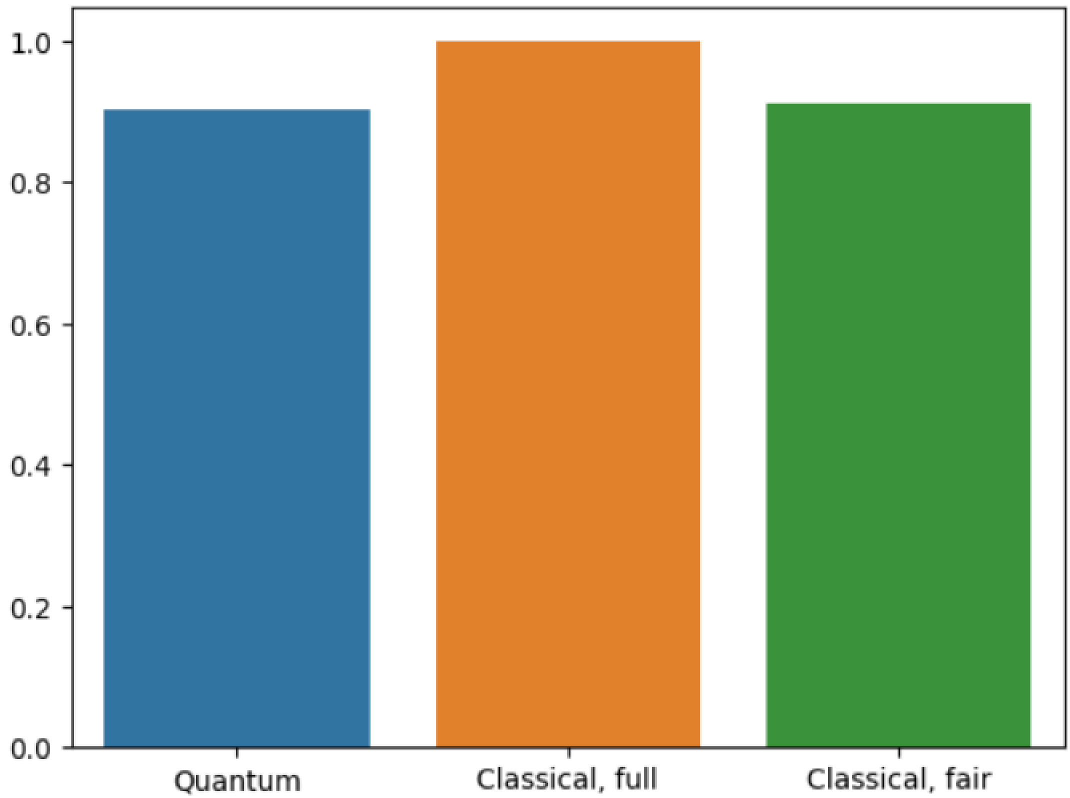

Figure 6.1: Comparison Graph

and deep learning architectures. For researchers and practitioners working on picture classification tasks, particularly in the fashion domain, this study adds to the body of knowledge in the field of machine learning and offers helpful insights.

6.2 Future Work

- **Algorithmic advancements:** Investigate and create cutting-edge quantum algorithms designed exclusively for binary classification jobs. Examine the possibilities of quantum support vector machines, quantum neural networks, and variational quantum algorithms to improve classification efficiency and accuracy even more.

- **Investigate hybrid models** that combine the benefits of traditional ML or DL models with those of quantum computing. Create frameworks that take use of how classical and quantum systems operate together to improve binary classification performance.

- **Feature extraction, dimensionality reduction, and data encoding**: are a few examples of jobs that can be performed using quantum computing techniques for data preprocessing. Examine the employment of quantum-inspired techniques to increase classification accuracy and input data quality.

- **Transfer learning and domain adaptation**: Look at the use of these concepts in the context of binary classification using quantum machine learning. Investigate how pre-trained quantum models can be modified or adapted to various domains or tasks, minimising the requirement for time-consuming training on fresh datasets.

- **Advancements in quantum hardware:** Keep track of developments in this field, such as the creation of more durable and error-tolerant qubits, enhanced connectivity between qubits, and improved noise reduction methods. Examine the potential effects of these developments on the functionality and scalability of binary classification tasks using TFQ and Cirq

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