Automated Medical Image Diagnostics using QML

Thirumalai M[1] Shisheer S Kaushik[2] Haris Ansari[3] Sumit Kumar[4]

M.Tech - Quantum Technologies
Indian Institute of Technology, Jodhpur
{M23IQT008[1], M23IQT006[2],M23IQT003[3] M23IQT007[4]}

Abstract

We extend the concept of transfer learning[3], widely applied in modern machine learning algorithms, to the emerging context of hybrid neural networks[4] composed of classical and quantum elements. We propose different implementations of hybrid transfer learning[1], but we focus mainly on the paradigm in which a pre-trained classical network is modified and augmented by a final variational quantum circuit. This approach is particularly attractive in the current era of intermediate-scale quantum technology since it allows to optimally preprocess high dimensional data (e.g., images) with any state-of-the-art classical network and to embed a select set of highly informative features into a quantum processor. We use the cross platform software library PennyLane to experimentally test a high resolution image classifier.

Contents

1 Introduction

In this project we apply a machine learning method, known as transfer learning, to an image classifier based on a hybrid classical-quantum network.Transfer learning is a well-established technique for training artificial neural networks [3], which is based on the general intuition that if a pre-trained network is good at solving a given problem, then, with just a bit of additional training, it can be used to also solve a different but related problem.As discussed in [2], this idea can be formalized in terms of two abstract networks A and B, independently from their quantum or classical physical nature.

2 Convolutional Neural Network

Convolutional Neural Network, a specialized type of artificial neural network designed for processing structured grids of data. It's predominantly used in analyzing visual imagery, such as photos and videos, due to its ability to retain spatial relationships within the data.

2.1 Convolutional Layers

These layers apply filters to input data through convolution operations. Filters help in detecting various features like edges, textures, and patterns within the image.

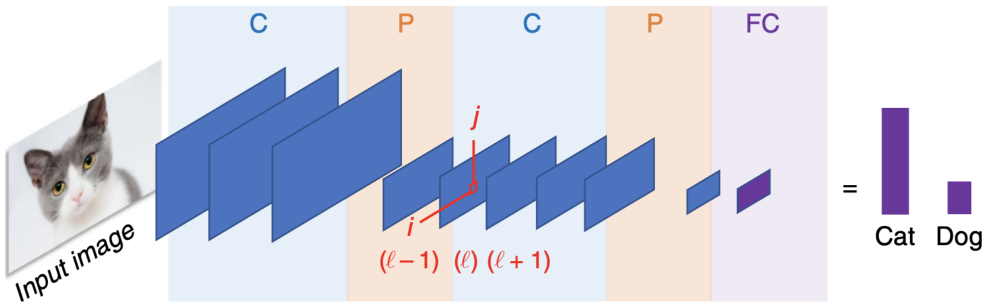

Figure 1: Convolutional Neural Network, image credits-PennyLane

2.2 Pooling Layers

Pooling reduces the dimensionality of each feature map generated by the convolutional layers, reducing computational complexity while retaining important information

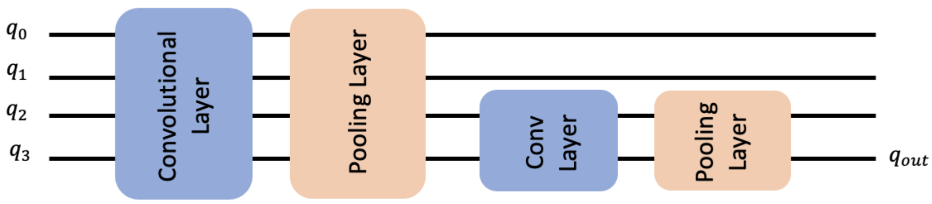

Figure 2: Layers in QCNN, image credits-PennyLane

2.3 Fully Connected Layers

These layers interpret the features extracted by the previous layers and make the final decision based on these features. They're typically found at the end of the network.

3 Quantum Convolutional Neural Network (QCNN)

A Quantum Convolutional Neural Network[2] (QCNN) is an extension of classical Convolutional Neural Networks (CNNs) designed to operate using quantum computing principles. QCNNs aim to leverage the unique properties of quantum computation to potentially enhance the capabilities of classical CNNs, especially in handling certain types of data or computational problems.QCNNs attempt to combine the principles of convolutional neural networks, which are highly effective in tasks like image recognition, with the power of quantum computing

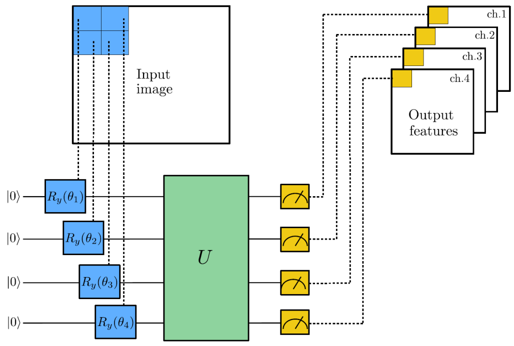

Figure 3: Quantum Circuit design, image credits-PennyLane

4 Problem Statement

In the realm of image classification, the endeavor to harness the capabilities of Quantum Convolution Neural Networks (QCNN) emerges as an intriguing challenge. Our mission is to delve into the unique convergence of quantum computing and image analysis. Specifically, we aim to implement a model classifying face image data set to predict disorders (i.e.,Parkinson's, Autism, etc), And to unravel the mysteries of QCNN architecture and its application in classifying images, while keeping a keen focus on the medical dataset and targeted towards disorders. Furthermore, we endeavor to draw comparisons between the QCNN and its classical counterpart, the Convolution Neural Network (CNN).

5 Dataset

We gathered a medical picture dataset for Autism. set of patient with no disorder and set of patient with disorder.

6 Code

Please find our code here. We have used packages from pennylane an open source platform which provides packages to build Quantum models. And other necessary python package for ML model.

6.1 Libraries

PennyLane PennyLane is a library for differentiable programming of quantum computers. It allows users to define quantum circuits and seamlessly integrate them with classical machine learning frameworks like TensorFlow.

PennyLane Templates This module provides pre-defined quantum circuit templates. In this code, RandomLayers is used to implement a random quantum circuit.

TensorFlow TensorFlow is an open-source machine learning library. In this code, it's used for building, training, and evaluating classical deep learning models.

Scikit-learn Scikit-learn is a machine learning library. The train_test_split function is used to split the dataset into training and testing sets.

7 Design and Implementation

7.1 Loading the dataset

We import the dataset. To speedup the evaluation of this demo we use only a small number of training and test images. Obviously, better results are achievable when using the full dataset.

7.2 Quantum circuit as a convolution kernel

We initialize a PennyLane default.qubit device, simulating a system of 4 qubits. The associated qnode represents the quantum circuit consisting of an embedding layer of local R_y rotations (with angles scaled by a factor of π), a random circuit of n_layers and a final measurement in the computational basis, estimating 4 expectation values.

7.3 Quantum pre-processing of the dataset

Since we are not going to train the quantum convolution layer, it is more efficient to apply it as a "pre-processing" layer to all the images of our dataset. Later an entirely classical model will be directly trained and tested on the pre-processed dataset, avoiding unnecessary repetitions of quantum computations.

7.4 Hybrid quantum-classical model

After the application of the quantum convolution layer we feed the resulting features into a classical neural network that will be trained to classify the dataset. We first initialize an instance of the model, then we train and validate it with the dataset that has been already pre-processed by a quantum convolution.

8 Results and Observation

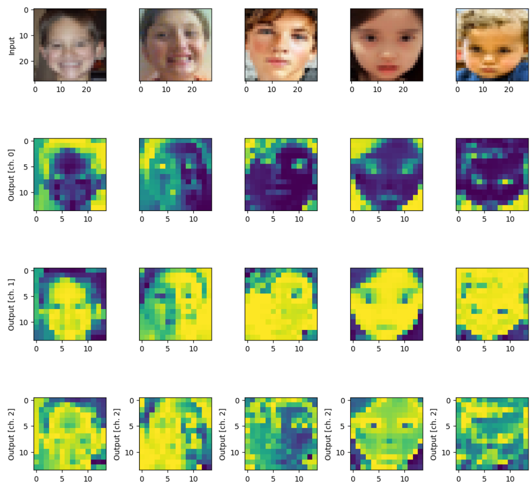

Figure 4: Preprocessed image dataset

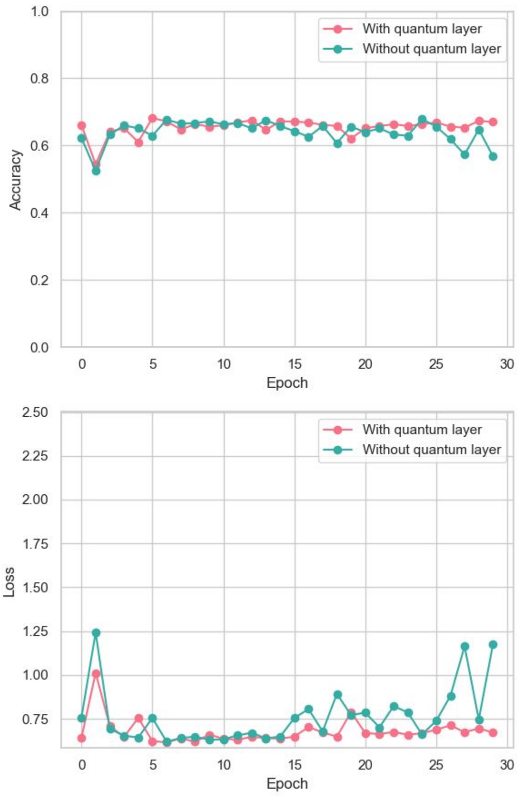

Figure 5: Efficiency plotted against classical

We can finally plot the test accuracy and the test loss with respect to the number of training epochs.It is evident from the results that the efficacy of the quantum mode has been enhanced in the majority of locations in comparison to the classical model. This is as a result of the quantum circuit's acceleration.

References

[1] Andrea Mari, Thomas R. Bromley, Josh Izaac, Maria Schuld, and Nathan Killoran. Transfer learning in hybrid classical-quantum neural networks. arXiv:1912.08278 (2019).

[2] Maxwell Henderson, Samriddhi Shakya, Shashindra Pradhan and Tristan Cook.Quantum Convolutional Neural Networks: Powering Image Recognition with Quantum Circuits. Submitted on 9 Apr 2019. arXiv:1904.04767

[3] Rajat Raina, Alexis Battle, Honglak Lee, Benjamin Packer, and Andrew Y Ng. Self-taught learning: transfer learning from unlabeled data. Proceedings of the 24th International Conference on Machine Learning*, 759–766 (2007).

[4] Ville Bergholm, Josh Izaac, Maria Schuld, Christian Gogolin, Carsten Blank, Keri McKiernan, and Nathan Killoran. PennyLane: Automatic differentiation of hybrid quantum-classical computations. arXiv:1811.04968 (2018).