Demonstrating Hybrid Quantum-Classical Neural Network

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

Raghav Juyal and Nithyanandan Kanagaraj
Department of Physics, IIT Hyderabad
ep20btech11018@iith.ac.in nithyan@phy.iith.ac.in

Objective

In this study, we test an implementation of a hybrid quantum-classical convolutional neural network on a dataset of chest X-ray images for classifying whether the patient has pneumonia or not.

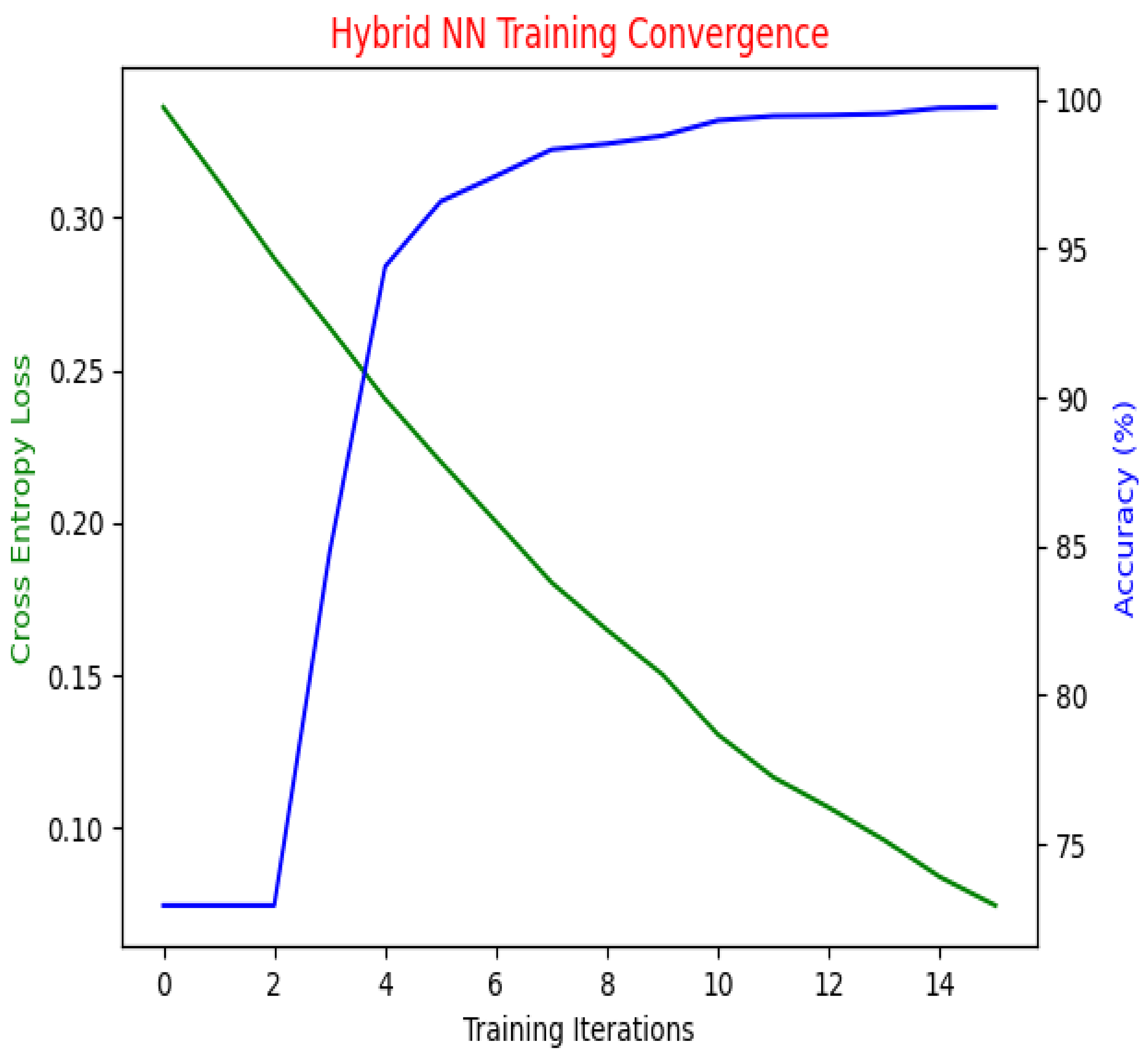
Architecture of the hybrid neural network

Layer (type: depth-index)	Output Shape	No. of Parameters
Conv2d: 1-1	[-1, 128, 636, 636]	9,728
Conv2d: 1-2	[-1, 128, 316, 316]	147,584
Conv2d: 1-3	[-1, 128, 154, 154]	409,728
Dropout2d: 1-4	[-1, 128, 77, 77]	- -
Linear: 1-5	[-1, 128]	97,140,864
Linear: 1-6	[-1, 2]	258
TorchConnector: 1-7	[-1, 1]	4
Linear:1-8	[-1, 1]	2

Total params	97,708,168
Trainable params	97,708,168
Non-trainable params	0
Total mult-adds (G)	28.42

Input size (MB)	4.69
Forward/backward pass size (MB)	515.69
Params size (MB)	372.73
Estimated Total Size (MB)	893.11

Results



Loss and accuracy of the hybrid model

Comparison

	Classical	Hybrid
Training Time(s)	4378.131	5848.856
Accuracy(%)	95.02	95.02

This comparison shows that the hybrid model can produce similar accuracy to the classical model. We note that the quantum layer is pretty simple but can be replaced by more complex layers as more development is done in quantum computers. We also note that since we are using a quantum simulator, the time for training the hybrid model is more.

Details of the dataset and network architecture

Here we use a dataset of chest X-ray images for classifying whether the patient has pneumonia or not.

There are 4077 training images and 582 test images.

Each image has the dimensions 640×640 and 3 colour channels(red, green, and blue).

The architecture of the hybrid quantum-classical convolutional neural network consists of 3 pairs of convolutional and pooling layers, a dropout layer to reduce overfitting, followed by 2 fully connected layers, the quantum layer, and a final linear layer.

The quantum layer was simulated with the aer simulator with the 'statevector' method.

The training data was divided into batch sizes of 8 the training was done over 16 epochs with a learning rate of 0.0001 and a cross-entropy loss function.

The training followed an increase in accuracy with the increase in epochs.

Conclusions and Future Work

- We have implemented a hybrid quantum-classical convolutional neural network that achieves similar accuracy to the classical convolutional neural network.
- In future work, we plan to implement and test more quantum machine learning and neural network algorithms on various datasets.