QPU Tasks, Summer school

Testing TQ quantum layers with IBM QPU

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Evaluating the performance of different TQ quantum layers for an IBM Quantum Processing Unit (QPU) and establishing best practice.

1 Introduction

This project is aimed at benchmarking hybrid quantum neural networks with different quantum layer architectures using the Hidden Manifold. The quantum layers tested are: parallel quantum network (PQN), quntum depth-infused network (QDI) and parallel exponential network (EFQ)

2 Dataset description

The Hidden Manifold problem is a classification task mimicing the idea, that the data is labeled on a manifold that is embedded in a space of different dimentionality.

Input vectors of m dimensions are sampled from a normal distribution in a low-dimensional space and labeled by a single-layer neural network initialised at random. The inputs are then projected to the final d-dimensional space. There are two different dataset collections in this task, one only varying the dimension of the input vectors while keeping the manifold dimension constant, while the other, vice versa, keeps the d constant and varies the dimensionality of the manifold.

In this project we decided to use the first collection with $d = 5$ and $m = 6$ while larger vector dimensions lead to use of larger models, which significantly increases training time.

3 Hybrid parallel quantum network

3.1 General information

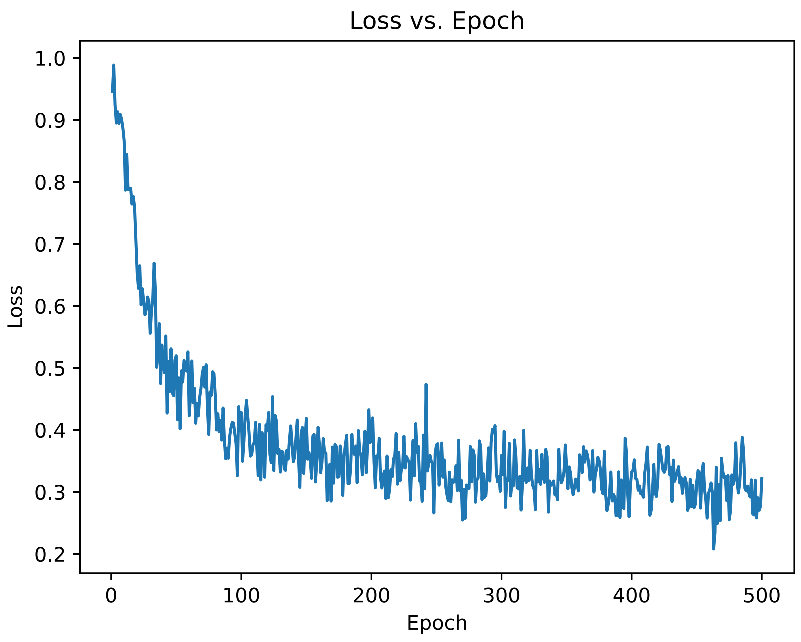
We propose the following architecture for Hybrid PQN networks: the input data go into a fully connected network, which then connects to the PQN Quantum circuit (or a few of them). The PQN quantum circuit consists of R_x rotation gates for input feature embeddings and repetitions of sets of R_z, R_y, R_z weighed rotation gates with CNOT gates for entanglement. After that each qubit is measured in Z axis and the result is forwaded to another FCNN.

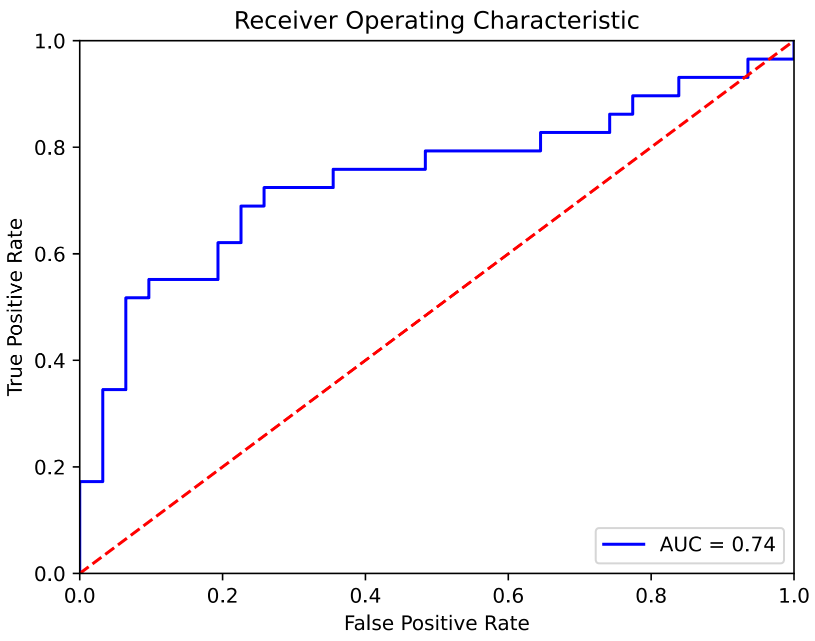
3.2 Architecture 1

The input FCNN consists of fully connected layers with sizes: 48-24-12 (in that particular order). The second dense layer's architecture is 64-32-16-8-4. In both networks we use batch normalization and dropout.

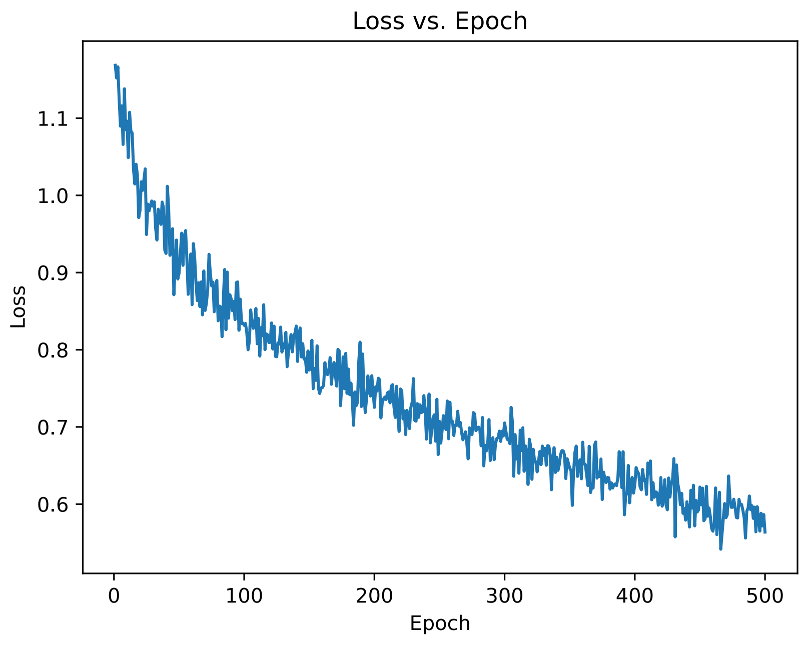
The quantum layer has 5 qubits and two repetitions of weighed gates, totalling 5544 trainable parameters.

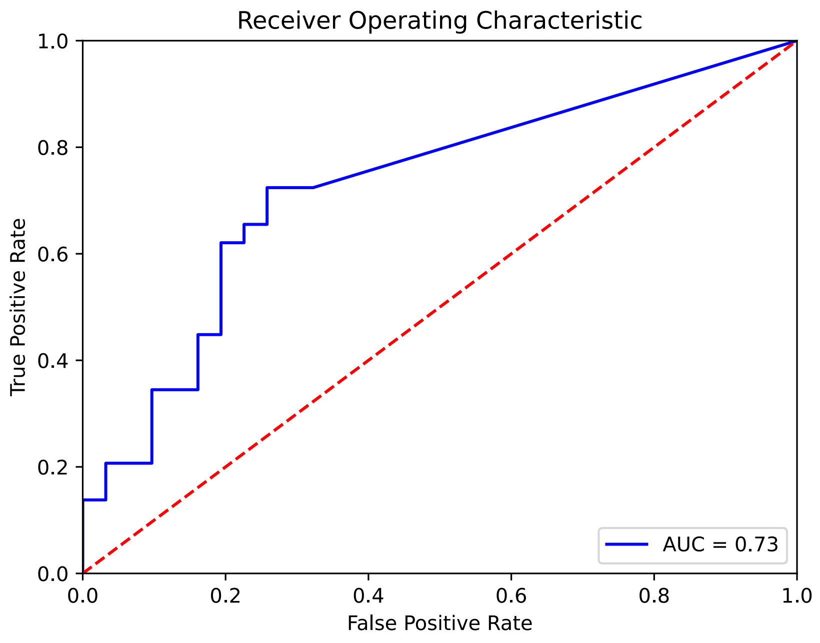
3.2.1. Noiseless case





3.2.2. Noisy case



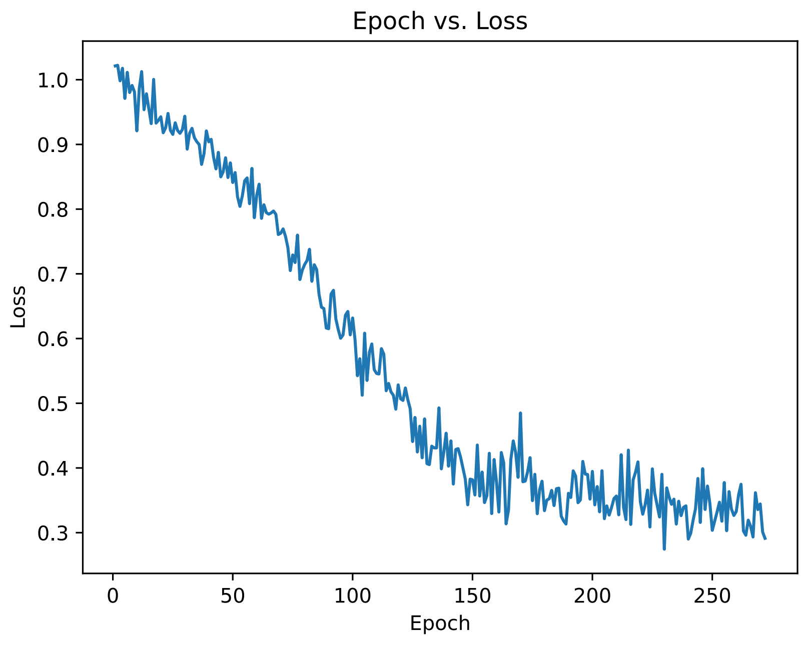


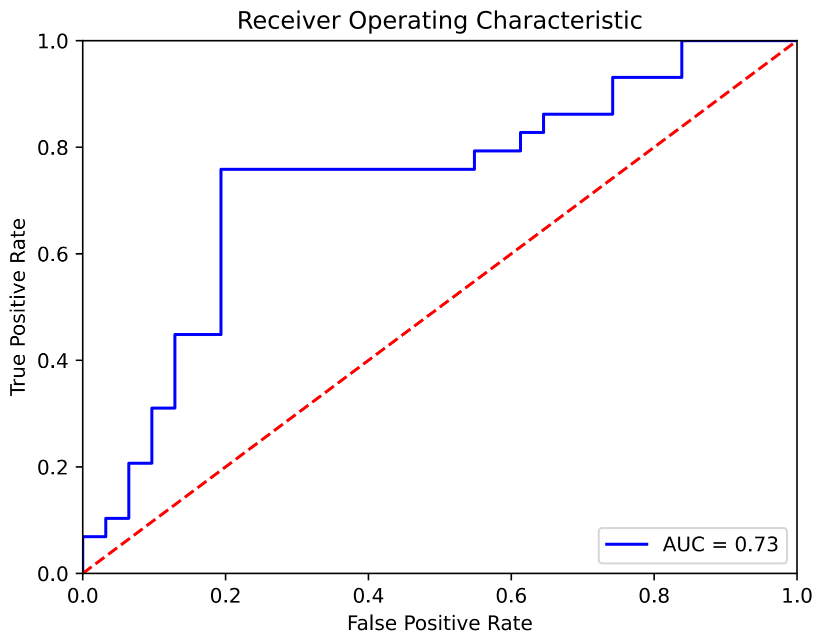
3.3 Architecture 2

Our HPQN enables support of multiply quantum circuits in parallel. In that case the output of the first FCNN is divided according to the number of quantum circuits and their sizes. Then the output of all quantum circuits are concatenated back together to be passed to the dense layer.

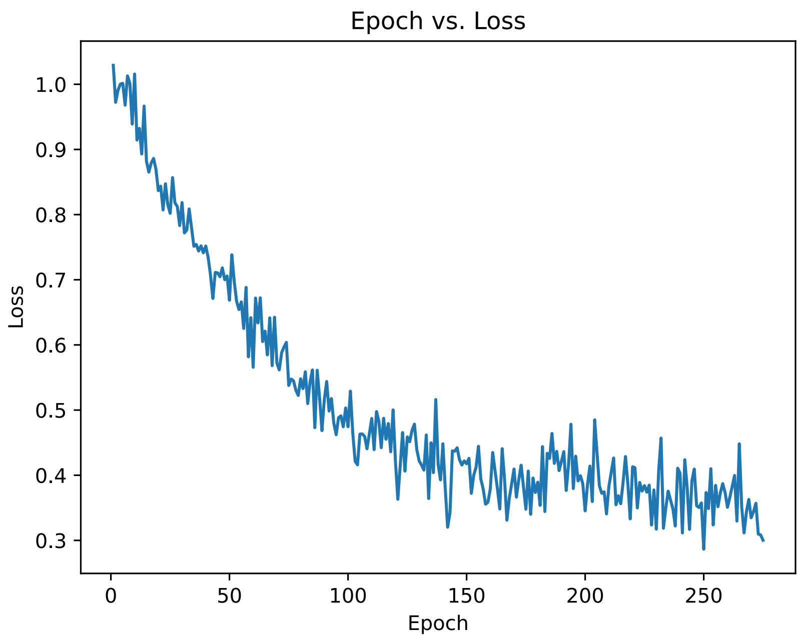
This particular architecture is analagous to the previous one, using the same dense layer sizes but with two parallel 4-qubit quantum circuits, keeping the number of weighed gate sets repetitions equal to 2.

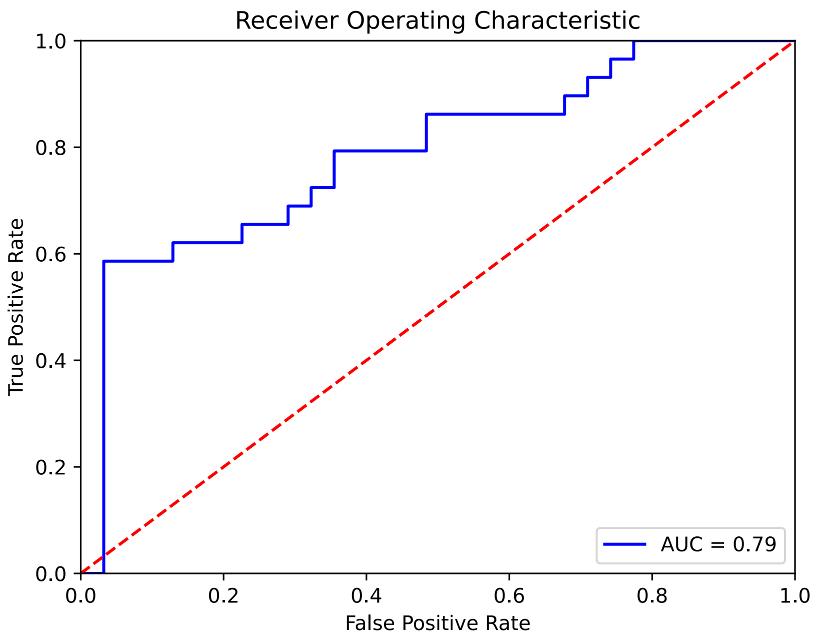
3.3.1. Noiseless case





3.3.2. Noisy case





4 Quantum depth-infused network

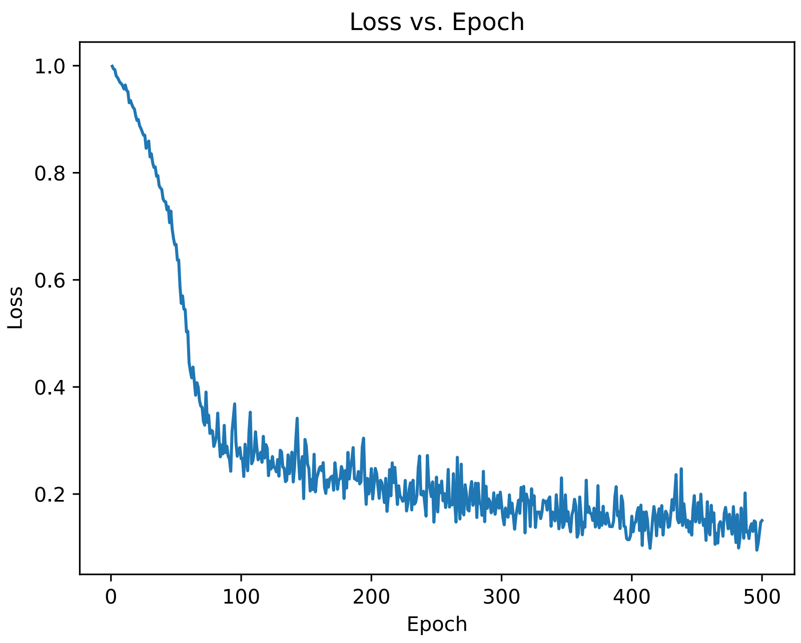
4.1 General information

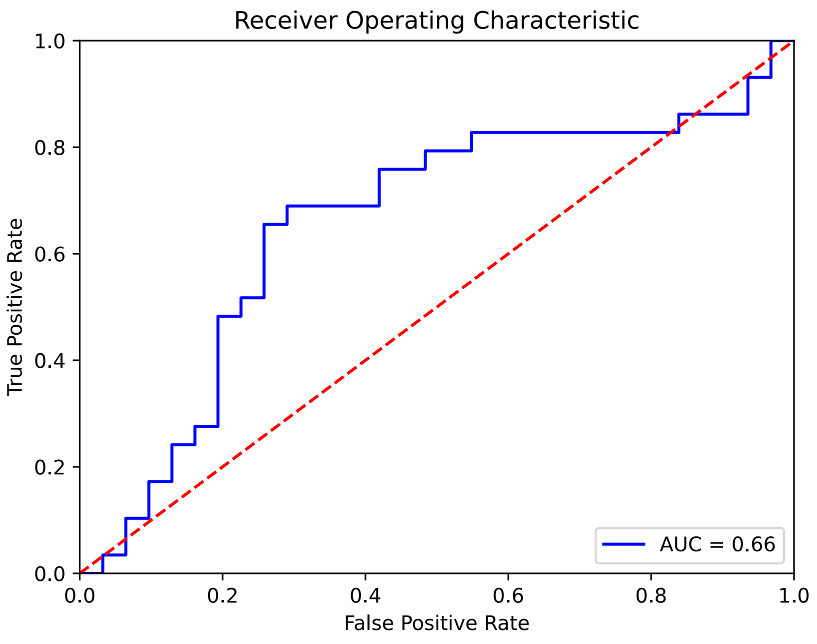
Hybrid QDI network consists of single FCNN and QDI quantum layer. The inputs go into the dense layers and then the results are forwaded to the quantum layer using rotation embedding. The QDI quantum circuit has the following architecture: first R_x weighed gates with CNOT gates are repeated i times. Then embedding R_z, weighed R_x (repeated n times) and CNOT gates are repeated j times. Then the first qubit is measured in the Z axis and passed as an output.

4.2 Architecture 1

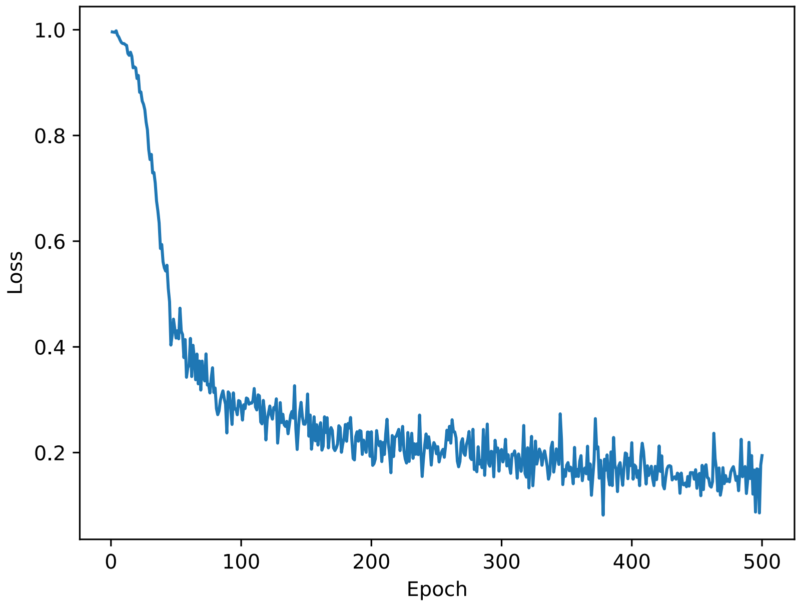
This architecture proposes FCNN with layer sizes 64-32-32-16-8. The QDI layer parameters are as following: $i = 1, n = 2, j = 2$. Total amount of trainable parameters -

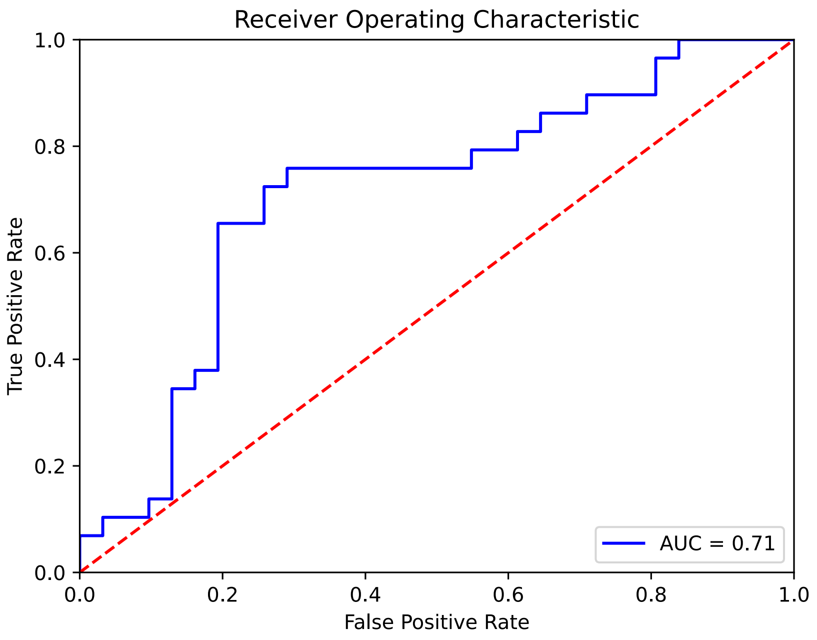
4.2.1. Noiseless case





4.2.2. Noisy case



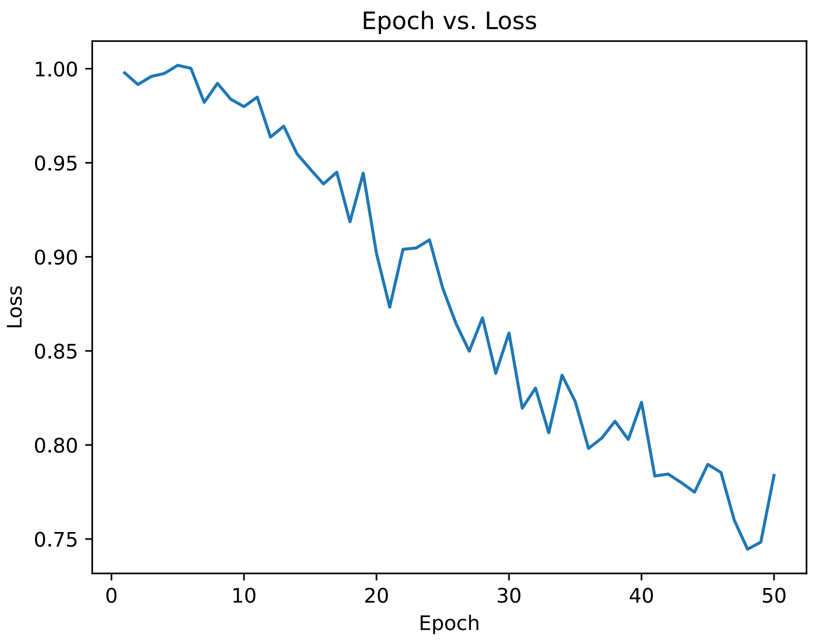


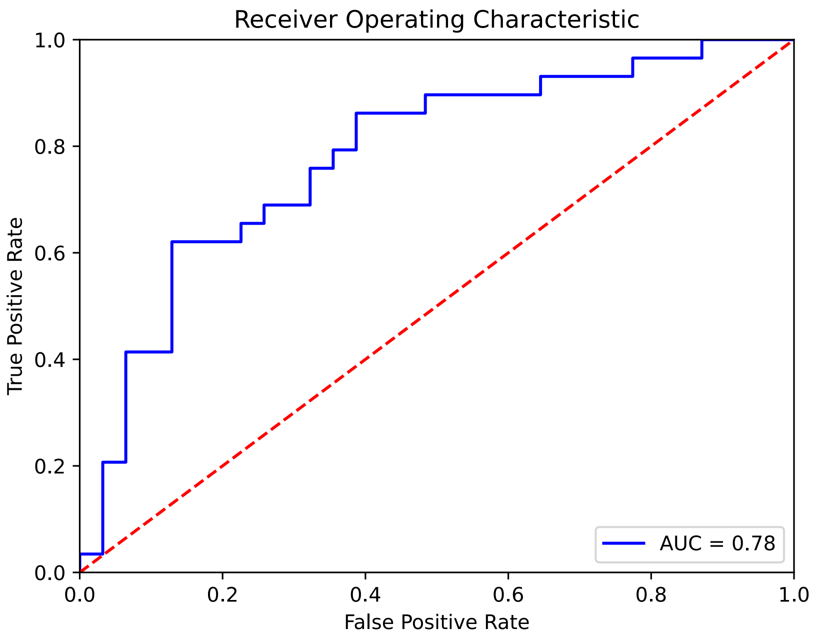
4.3 Architecture 2

QDI (on par with EFQ) enables the deepest quantum circuits architecture, so we decided to train a model with a larger number of parameters using less epochs.

For this architecture the parameters of the quantum ciricuit are 3, 2, 5 for i, n and j accordingly. The dense layers sizes were also slightly changed with the whole model totalling 17860 parameters.

4.3.1. Noiseless case





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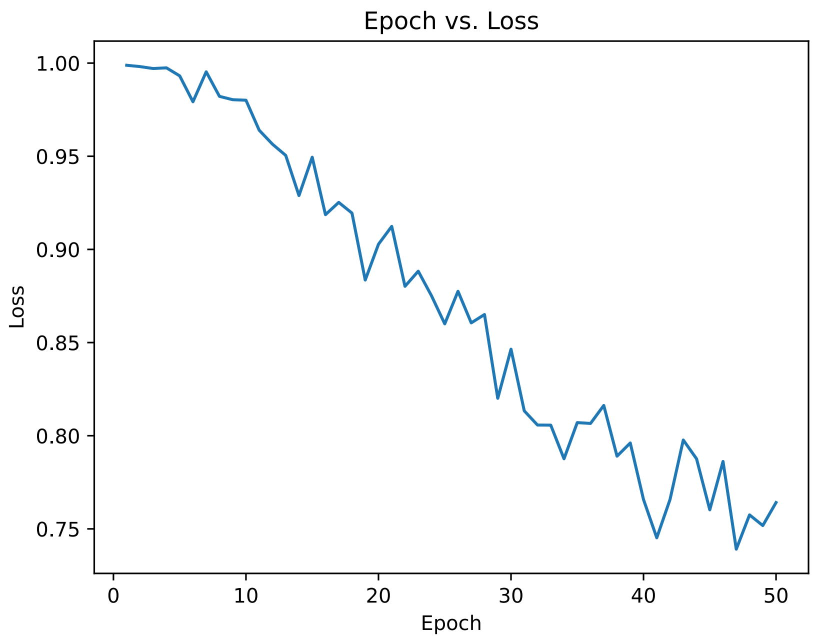
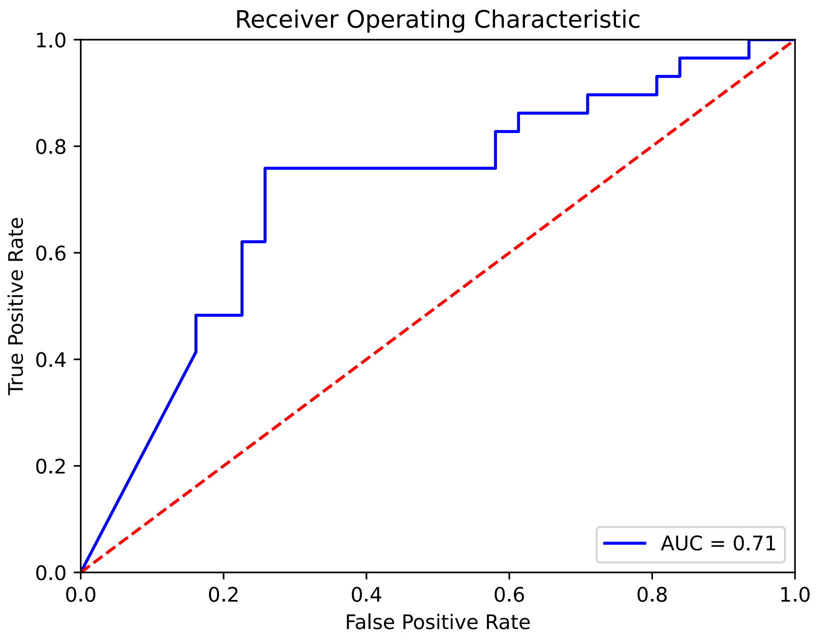




5 Parallel exponential network

5.1 General information

Analogous to the Hybrid QDI network this architecture consists of a fully connected neural network followed by a EFQ quntum circuit.

Compared to aforementioned architecures the EFQ architecture has a unique input embedding method. If we enumerate all the qubits from "top to bottom"for 1 to n, the rotation of the embedding R_x gate on the ith wire will be $(2^{n-1}+1)x$, where x is the the input.

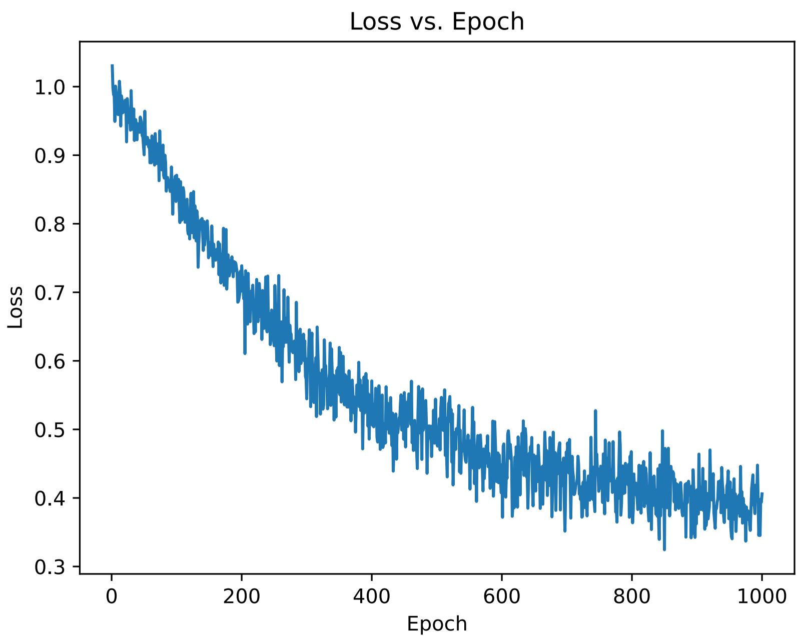
As weighted gates we use the following architecture: two sets of R_y, R_z, R_x (in that particular order) gates divided by CNOT gates connecting every wire paired.

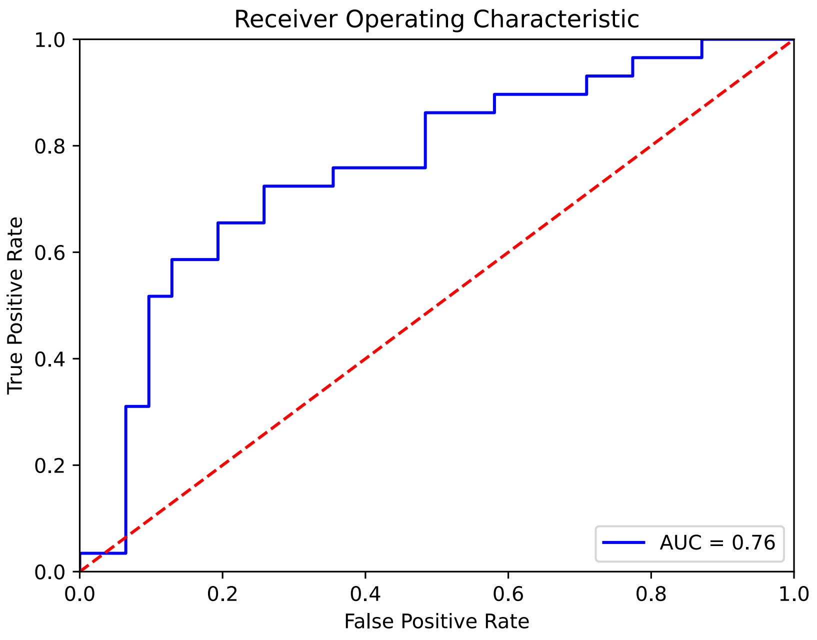
Thus the EFQ quantum circuit consists of weighted gates and embedding gates followed by each other ending with a set of CNOT gates.

5.2 Architecture 1

The first network consists of input dense layers with sizes 64-32-16-8-4 and a 2-qubit EFQ quantum circuit with 3 sets of weighted gates, totalling 3458 parameters.

5.2.1. Noiseless case





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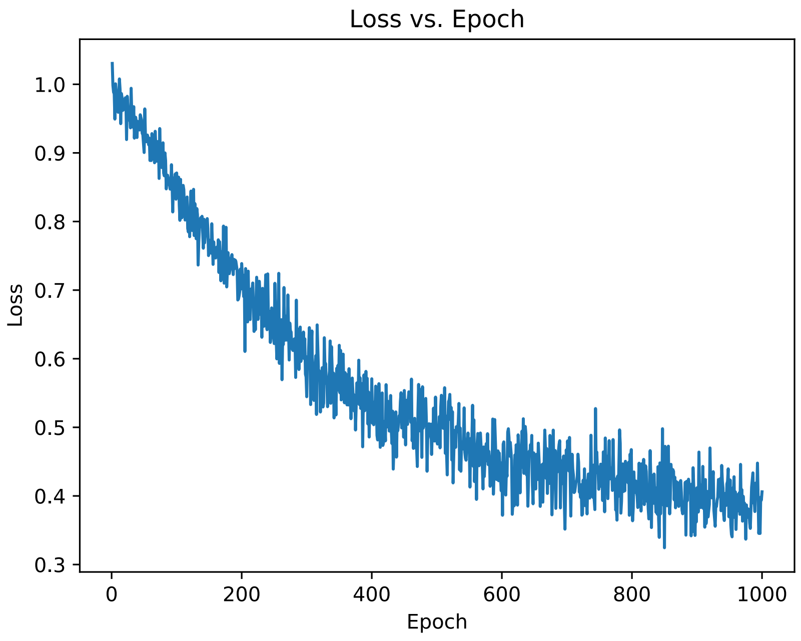

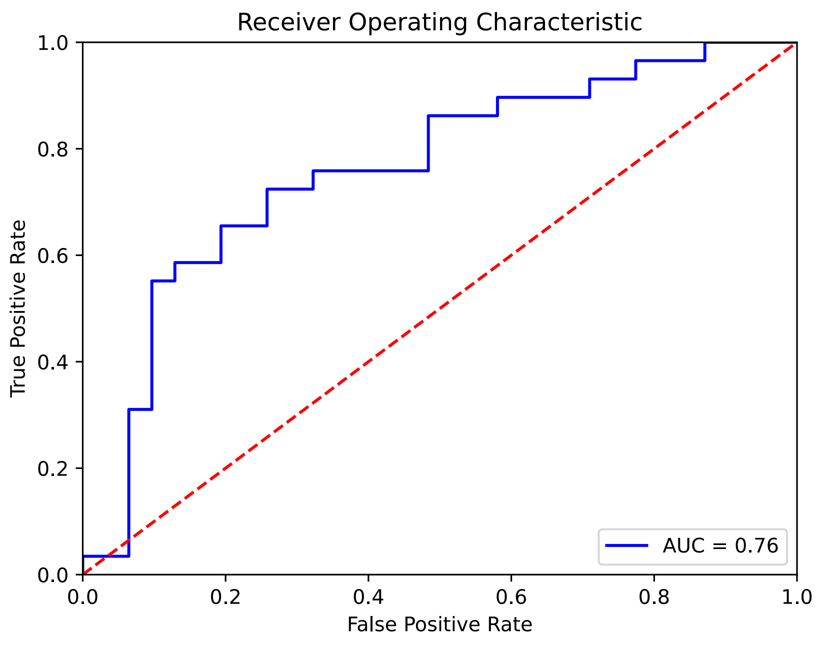

6 Conclusion

6.1 HQNN vs. classical FCNN

We have successfully trained and verified 3 different HPQN architectures. The results show that hybrid quantum neural networks performance is on the same level or even better than of the fully connected architectures with the same amount of parameters.

6.2 Noise influence

As we can see in some cases noise can slow down the training process and lead to bigger loss values in the same amount of epochs, however in case of small models and long training times (500 epochs took 16 hours) it's influence is not crucial. On the other side larger models training with less epochs suffer the most from the noise interference.

It should be noted that when emulating noise we did not enable readout errors for faster computing times.

6.3 Improvement points

To improve this project following steps can be made:

- Benchmark more different architectures and hidden manifold dataset collections for a wider range of data
- Verify the results with a real device
- Enable full-scale gpu support for Qiskit Algorithms gradient framework