



QSTH 2022

Quantum Science & Technology Hackathon

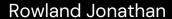




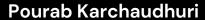


The Team "Geek Squad"





Web3 & Metaverse Developer Cloud Engineer MLOps Consultant



Innovation Consultant
Technical Architect
Data Scientist



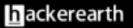
THEME Financial Services





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Prototype Submission





Point of View

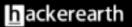
How do I future-proof fake bank note detection for Tier 2 & 3 cities who don't have access to accurate fake bank note machines?

India has long been a cash economy and most people in the country still follow the cash transactions route.

Even with rise in digital payments in the Tier-I cities and adoption of contactless payment during the pandemic, semi-urban and rural areas are still heavily reliant on cash transactions. This makes India more prone to hazardous counterfeiting activity.

The pandemic has also triggered many households towards hoarding cash. Rise in counterfeit currency was one of the reasons why Demonetization came into effect

Current image processing techniques used in Fake Note Detection Machines are still only up to 80% accurate. Counterfeiting technology also plays catch up to make indistinguishable fake notes







Our Solution

A Hybrid Quantum Classical machine learning model for classification of even the most indistinguishable fake bank notes from real ones

Classical Machine Learning models exist but take a long time to train, and current models go upto 80% accuracy only in production scenarios with standard UV and Image processing techniques

Our QVC (Quantum Variational Circuits), is based on a Quantum classical machine learning model to use Ansatz encoders to do bank note <u>authentication</u>

We will attempt to run these QVCs on real Quantum hardware to benchmark the results







The Dataset used

A banknote authentication dataset

- Data were extracted from images that were taken from genuine and forged banknote-like specimens. For digitization, an industrial camera usually used for print inspection was used.
- The final images have 400x 400 pixels.
- Due to the object lens and distance to the investigated object gray-scale pictures with a resolution of about 660 dpi were gained.
- Wavelet Transform tool were used to extract features from images.

Courtesy: University of Applied Sciences

https://archive.ics.uci.edu/ml/datasets/banknote+authentication

Dataset Information

- Total examples: 20,468 Dimensions: 112
- PCA down to: 4 dimensions
- Train set size: 100
- Test set size: 2,000

Attribute Information

- 1. variance of Wavelet Transformed image (continuous)
- 2. skewness of Wavelet Transformed image (continuous)
- 3. kurtosis of Wavelet Transformed image (continuous)
- 4. entropy of image (continuous)
- 5. class (integer)







Technology Stack



Python

A language that we all love and know



Quantum Hardware

An **Actual** 7 Qubit Quantum Computer



Qiskit

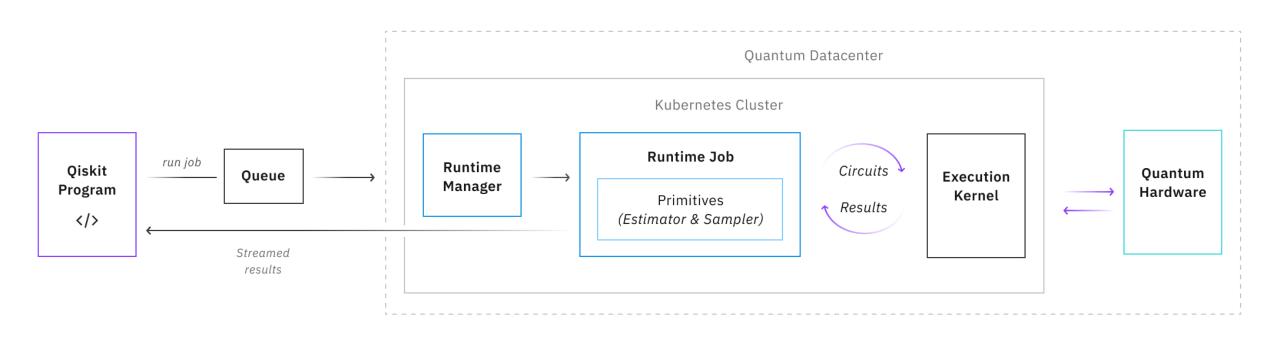
Library for creating Quantum Logic Circuits







Methodology

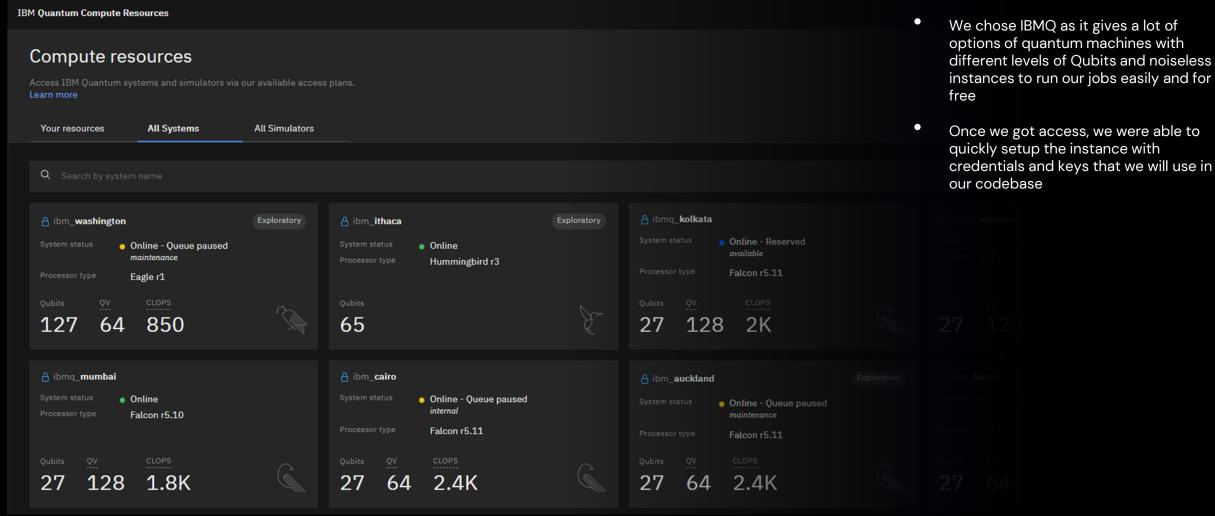








Setting up an IMBQ instance



hackerearth





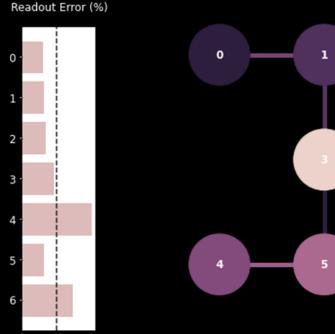
Choosing our Quantum Hardware

CNOT error rate (%) [Avg. = 0.887]

1.4

0.8

ibm_oslo Error Map



H error rate (%) [Avg. = 0.035]

0.056

Qubits Quantum Variance

32

CLOPS

2.6K

- We selected the IBMQ Oslo instance for our hackathon. It has relatively lower CNOT and H error rates.
- Since Quantum machines are not truly noiseless, CNOT (Gate) and H (Hamiltonian) error rates are results of benchmarking done by Quantum providers to calculate and tolerance for quantum operations
- These are generally losses due to the semiconductors used in the gates
- Hence, we tried to take this into consideration as we selected the optimum quantum instance for running our jobs

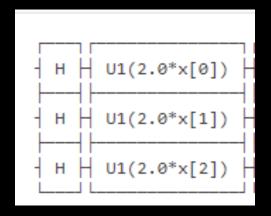


0.032

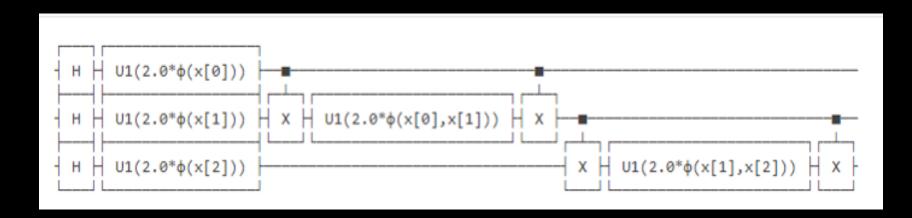




Converting Classical Data to Quantum Data



- The first order Pauli Z-evolution circuit.
- A first order diagonal expansion is implemented using the ZFeature Map where |S| = 1.
- The resulting circuit contains no interactions between features of the encoded data, and therefore no entanglement



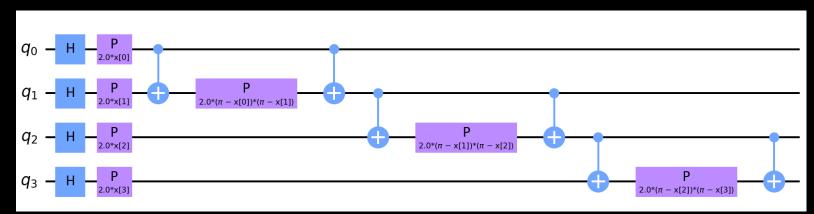
- The Second-order Pauli-Z evolution circuit.
- The ZZFeatureMap feature map allows |S| ≤ 2
- Interactions in the data will be encoded in the feature map according to the connectivity graph and the classical data map.
- Here ϕ is a classical non linear function



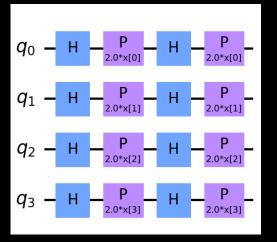




Our Variational Quantum Circuit (VQC)

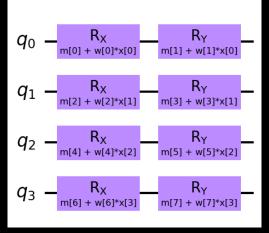


ZZ feature map for 4 dimensions & linear entaglement



Z feature map for 2 dimensions

h ackerearth



Angular embeddings

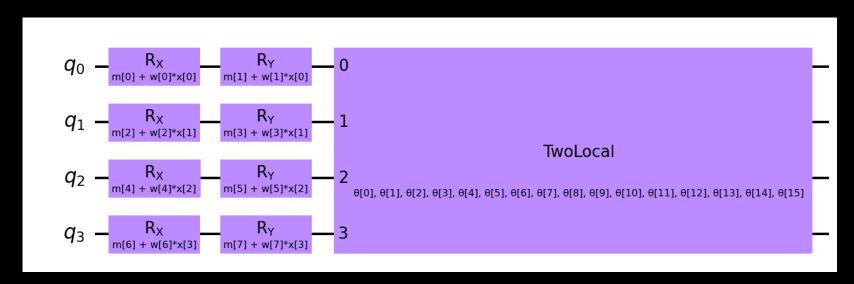
- We begin by performing certain operations that will help us work the classical data into quantum circuits.
- One of the steps is called data embedding, which is the representation of classical data as a quantum state in Hilbert space via a quantum feature map
- Similar to a classical feature map, in that it helps us translate our data into a different space, in this case quantum states, so that we can input it into the algorithm.
- We are producing a quantum circuit in which the parameters depend on the input data
- Once we've applied our feature map, a quantum computer can analyze the input data in this feature space, and a classifier can find a hyperplane to separate the data





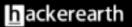
A Starting point for the first ML iteration

Ansatz = an assumption about the form of an unknown function which is made in order to facilitate solution of an equation or other problem.



Ansatz for Optimization with Two Locals for Linear entanglement

- In the context of variational circuits, an ansatz usually describes a subroutine consisting of a sequence of gates applied to specific wires
- It typically provides an initial estimate or framework to the solution of a mathematical problem, and can also take into consideration the boundary conditions
- The ansatz is the first guess. A starting point.
 Of course, if the starting point is good, so will the result
- The two-local circuit is a parameterized circuit consisting of alternating rotation layers and entanglement layers. The rotation layers are single qubit gates applied on all qubits

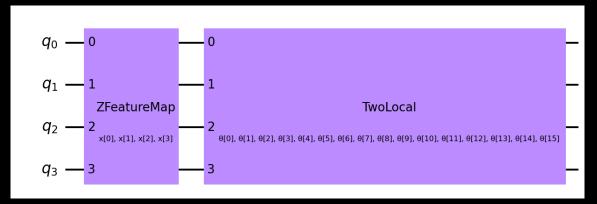






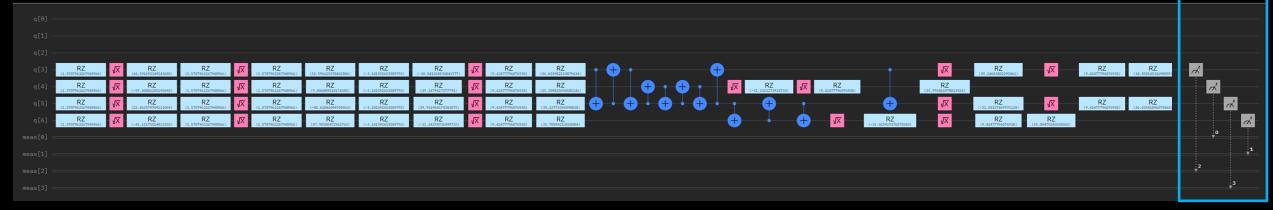
How we measured our QVC during training

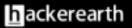
Pauli Measurement = The notation of Pauli measurements references this unitary equivalence by identifying X,Y,Z X , Y , Z measurements as equivalent measurements that one could do to gain information from a qubit



We defined our measurement circuit with Pauli Operators and then measured the final states for each iteration while training our Quantum Machine learning model











Training our Quantum Machine Learning Model

```
# to run on hardware
max itr = 50 <
spsa opt = SPSA(maxiter=max itr, callback=callback)
loss recorder = []
initial point =
np.random.random((len(list(ansatz_tl.parameters) +
list(m params)),))
vqc = NeuralNetworkClassifier(
    neural network=qnn hardware,
    loss=CrossEntropyLoss(), # log of ...
    one hot=True,
   optimizer=spsa opt, 4
    initial point=initial point,
x_train_norm = np.array(
    [x / np.linalg.norm(x) for x in x train]
  # normalizing or not ... can depend on the data set you
can try both
vqc = vqc.fit(x train norm, y train 1h)
```

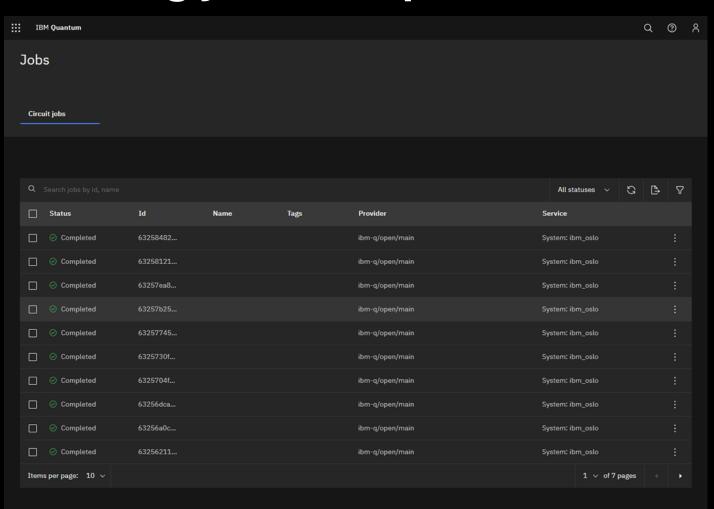
- We ran 50 iterations on our chosen IBMQ
 Quantum hardware
- O Ansatz was our starting point for training
- Simultaneous Perturbation Stochastic Approximation (SPSA) optimizer was used.

It is an gradient descent method for optimizing systems with multiple unknown parameters. As an optimization method, it is appropriately suited to large-scale population models, adaptive modeling, and simulation optimization.





Running jobs on quantum hardware



1 - 1.224287567138672 2 - 1.2125838565826417 3 - 1.1953830337524414 4 - 1.1845074081420899 5 - 1.1858576679229735 6 - 1.173168363571167 7 - 1.1670312309265136 8 - 1.1567787075042724 9 - 1.1542248058319091 10 - 1.143143253326416 11 - 1.1368250751495361 1.136270751953125 13 - 1.1263054180145264 14 - 1.1141995334625243 15 - 1.1134985637664796 16 - 1.1041170120239259 17 - 1.100945520401001 18 - 1.0901220989227296 19 - 1.0867064571380616 20 - 1.083990306854248 21 - 1.0843643474578857 22 - 1.072239761352539 23 - 1.0669044208526612 24 - 1.0597650051116942 25 - 1.0681822490692139 1.0540321254730225 27 - 1.0508317279815673 28 - 1.0484849643707275 1.0474994564056397 30 - 1.0401480197906494 1.0439655780792236 32 - 1.025972557067871 33 - 1.0402096557617186 34 - 1.037293872833252 35 - 1.0355580139160157 36 - 1.0265463161468507 37 - 1.0221664428710937

38 - 1.0338868713378906 39 - 1.0303220081329345 40 - 1.0205224227905274

- Each iteration for our model training ran successfully on the IBMQ instance
- After 50 iterations, we recorded the measurements from our variational circuit

Training Scores

Training Set

0.81

Test Set

0.515







Classical vs Quantum Result Comparision

Classical SVM

Training Set

0.74

Test Set

0.75

Classical ANN (20 Hidden Layers) with Sigmoid Activation

Training Set

0.71

Test Set

0.76

Quantum SVM

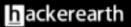
Training Set

0.81

Test Set

0.515

*and this is inclusive of semiconductor error rates as of quantum hardware today







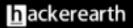
Conclusion

- We have successfully made a Classical-Quantum Hybrid Machine Learning Implementation for a real world problem using a Bank Note Authentication Dataset
- We are very happy that we managed to pull off something so advanced, all thanks to everyone who guided and mentored us
- To run this on an actual Quantum Hardware, was very exciting and a good learning experience
- We hope that this makes an impact and meets the hackathon requirements

Ending Question: Was Quantum Machine Learning necessary for this use case?

In context of where Quantum Computing is today, it nearly reaches the accuracy of classical models due to the quantum entropy and errors that are still there due to near perfect semiconductors used in the Quantum Hardware

As more innovations happen around both GPUs, TPUs (for classical), and semiconductor research (for Quantum), it will be a good fight between both compute systems and approaches. But we hope our expectations from quantum bears fruit and soon gets evangelized and democratized all over the world







Societal Impact

- Waiting or ignoring quantum computing might place intellectual property (IP) and patent portfolios at risk. Early organizations will have the competitive advantage by patenting quantum inspired innovations within their specific domains
- Proving that we can slowly but surely progress towards using Quantum for actual business use cases

Future Scope

- Because of the nature of Quantum Computers, we can max go up to using 20 qubits now. As more sophisticated and noiseless quantum machines are available, we can try productionizing our solution
- Future plans are to also explore different popular models like Credit Risk analysis, and stock time series forecast on a quantum machine and measure the results







Thank You

See you in the next round!

