

Quantum Machine Learning for Solar Panel Fault Detection

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PROGRAM: IRES UCY

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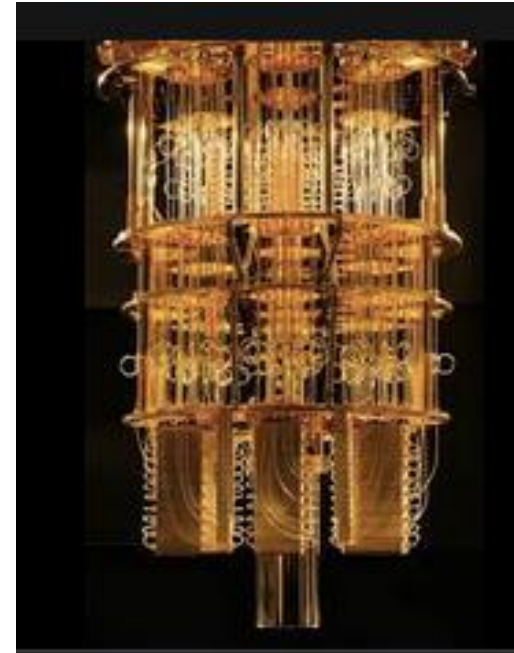


Presentation Agenda

- Problem statement
- Pre-training
- Previous work
- Proposed solution
- Algorithms/circuits
- Challenges of QML vs. CML
- Results
- Conclusions
- Next steps
- Reflection
- References

Problem Statement

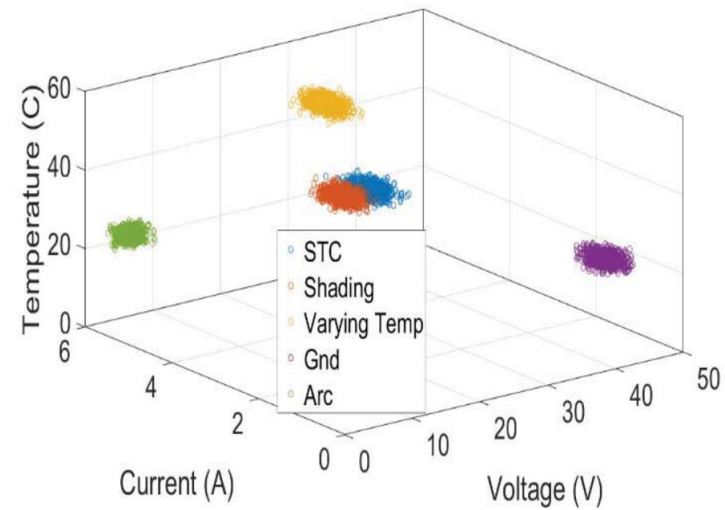
- Fault detection for photovoltaic arrays
 - Faults lead to efficiency issues in arrays
 - Machine learning can identify PV faults
 - Arrays can be reconfigured
- Quantum ML
 - New paradigm in computing
 - Applications in ML
 - Research into QML for this problem can be expanded on



From <https://www.neowin.net/news/quantum-supremacy-might-not-have-been-achieved-by-google-and-sycamore-after-all-says-ibm/>

Pre-Training

- General ML training in Python and Matlab
- Introduction to PV faults
- Focused training in three ML models
 - Logistic Regression
 - Support Vector Machines
 - Neural Networks
- Quantum ML training



From [1]

Previous Work

- *Machine Learning for Solar Array Monitoring, Optimization, and Control* [1]
- *Quantum Machine learning using Quantum Simulators* [2]
- *Solar Array Fault Detection Using Neural Networks* [3]
- *Quantum Neural Network Parameter Estimation for Photovoltaic Fault Detection* [4]

Proposed Solution

- Implement quantum and classical models
- Test using specifically labeled fault data
 - Short circuit vs. standard test conditions
- Compare quantum vs. classical

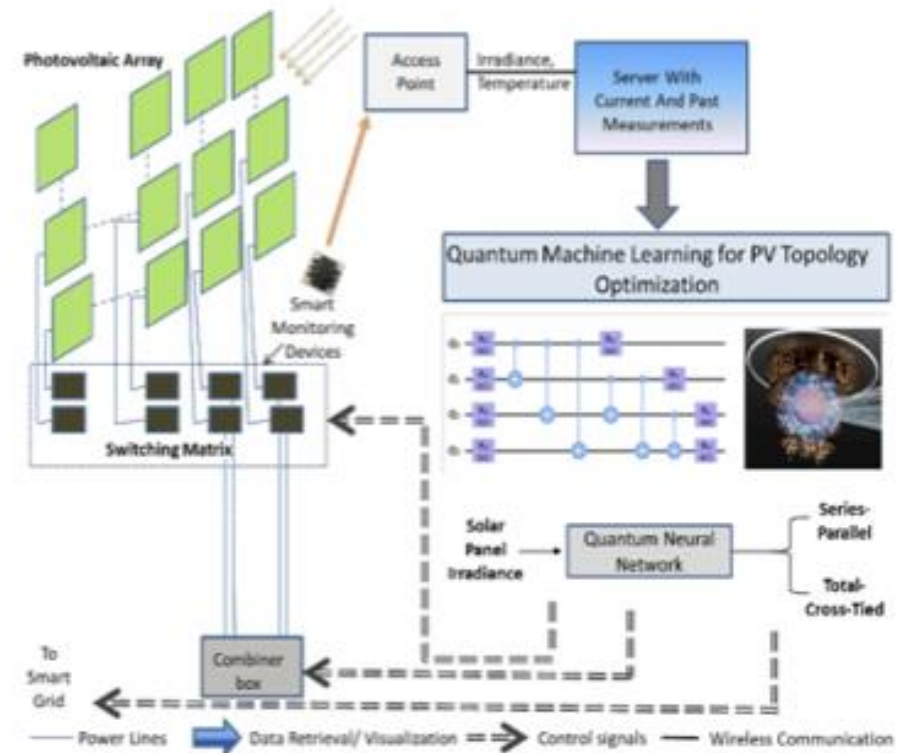
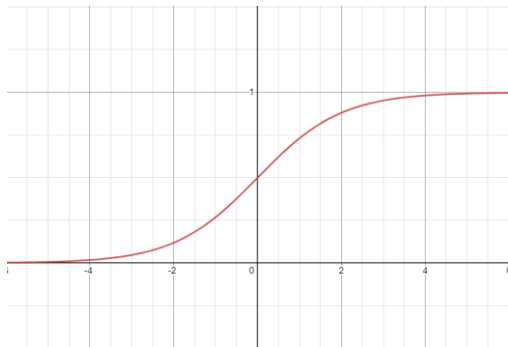


Figure from [4]

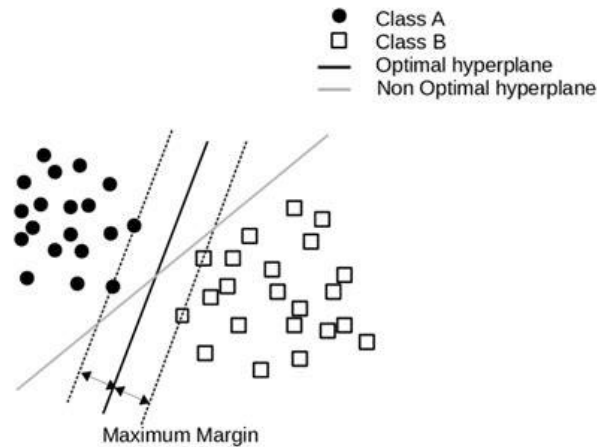
Circuits/Algorithms

- Classical Algorithms
 - Logistic Regression
 - Support Vector Machine
 - Neural Network

$$\text{Sigmoid}(x) = \frac{1}{1 + e^{-\theta x}}$$

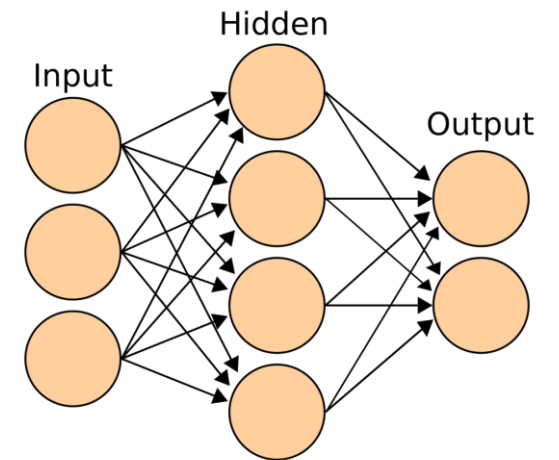


$$K(x, x') = e^{-\gamma \|x - x'\|} \quad \gamma = \frac{1}{n \text{ features} * \sigma^2}$$



From https://www.researchgate.net/figure/Support-Vector-Machine-example_fig4_313851520

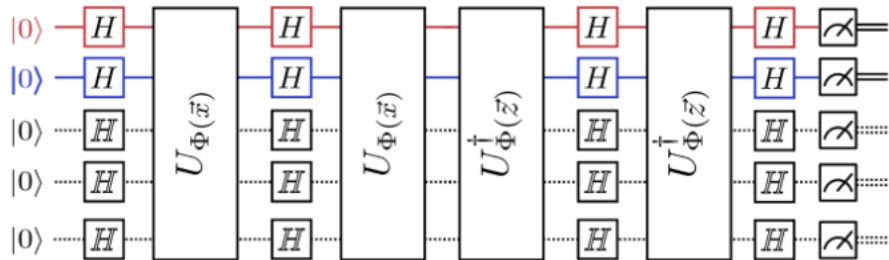
$$f(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{if } x \geq 0 \end{cases}$$



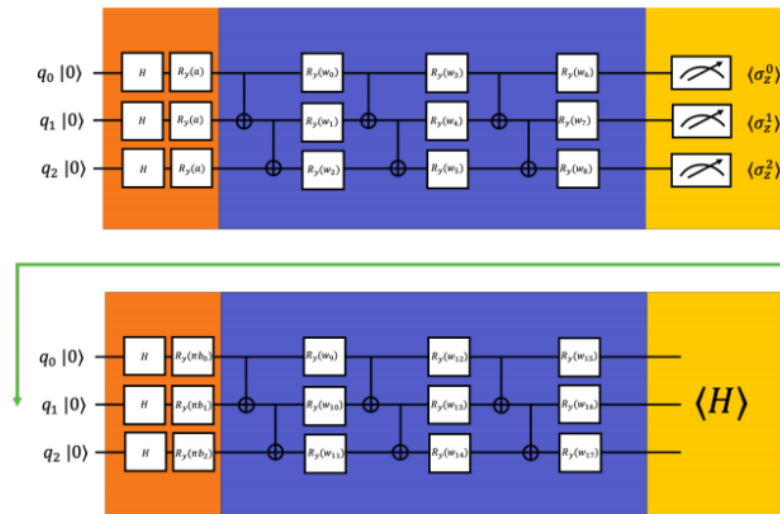
From <https://www.sitepoint.com/keras-digit-recognition-tutorial/>

Circuits/Algorithms

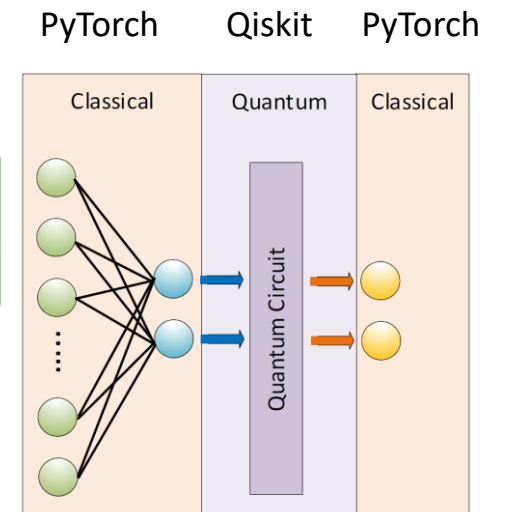
- Quantum Algorithms/Circuits
 - QSVM
 - QNN



From <https://medium.com/mit-6-s089-intro-to-quantum-computing/quantum-support-vector-machine-qsvm-134eff6c9d3b>



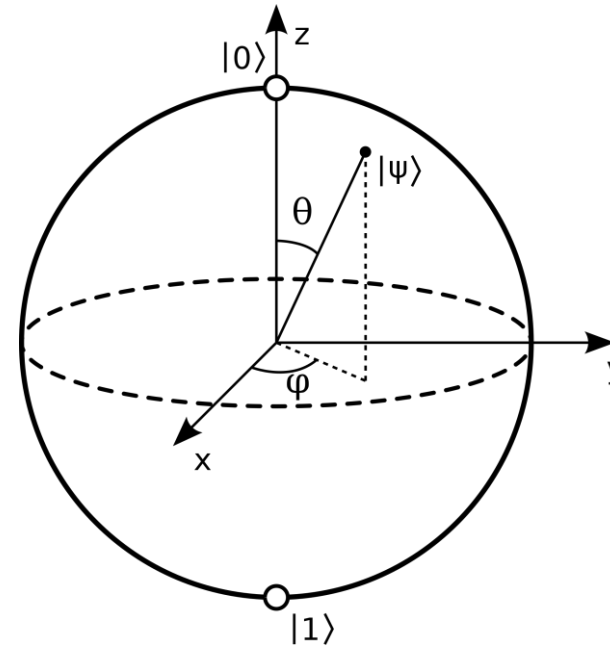
From <https://medium.com/qiskit/implement-a-hybrid-quantum-classical-neural-network-with-qiskit-7f732ed3b42a>



From [4]

Challenges of QML vs. CML

- Simulating Quantum is slow
- More hyperparameters
 - Shots
 - Types of Simulators
 - # of qubits
 - Learning rate
- Quantum is confusing



From https://en.wikipedia.org/wiki/Bloch_sphere

Results

Logistic Regression

Predicted Labels	Short Circuit	1338	143
	No Faults	195	1332
	True Labels	Short Circuit	No Faults

Accuracy: 88.76%

Hyperparameters:
Saga solver, l1 penalty

SVM

Predicted Labels	Short Circuit	1380	109
	No Faults	153	1366
	True Labels	Short Circuit	No Faults

Accuracy: 91.29%

Hyperparameters:
RBF kernel

Neural Network

Predicted Labels	Short Circuit	1451	89
	No Faults	60	1408
	True labels	Short Circuit	No Faults

Accuracy: 95%

Hyperparameters:
Two hidden layers, 300
nodes each, relu activation,
adam solver

Results

QSVM

Predicted Labels	Short Circuit	1987	161
	No Faults	115	2034
	True Labels	Short Circuit	No Faults

Accuracy: 94%

Hyperparameters: 2 qbits,
1024 shots, state vector
simulator

QNN

Predicted Labels	Short Circuit	105	25
	No Faults	760	829
	True labels	Short Circuit	No Faults

Accuracy: 50-60%

Hyperparameters: 2 qbits, 2
hidden layers, 256 shots, .03
learning rate, Sigmoid activation
function, QASM simulator

Conclusions

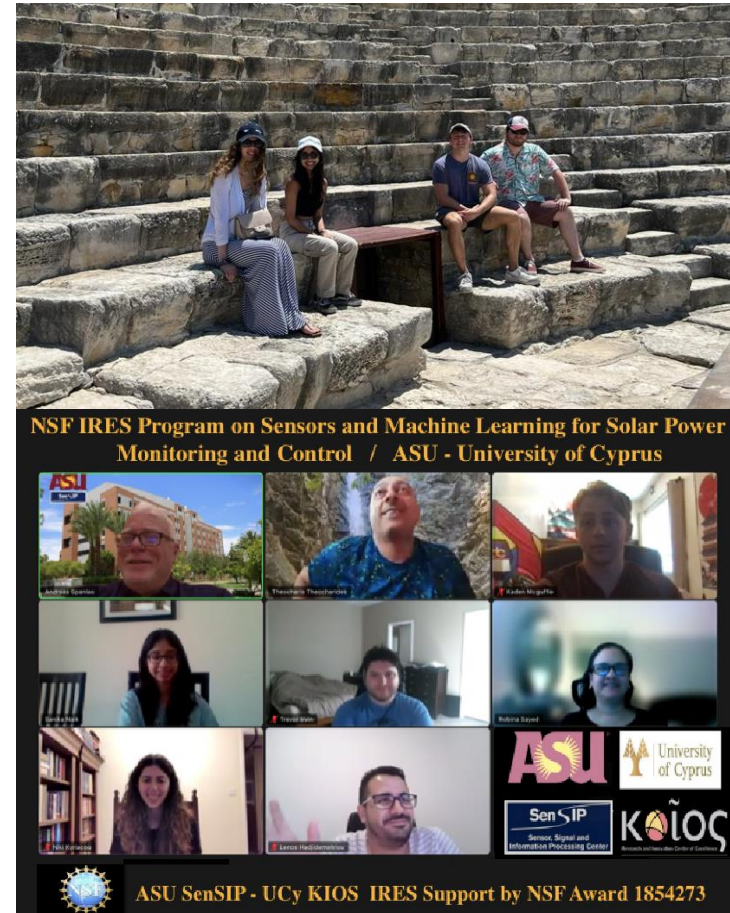
- Achieved good results on the QSVM within the simulator
- Results achieved were superior to the classical model
- The Quantum Neural Network performed poorly
 - Tests in similar quantum research yielded results ~90%
- Inconsistent results warrant further examination

Next Steps

- Attempt further tests with QNN
- Monte Carlo simulations
- Tests on actual quantum computers
- Work with a real, organic solar data set

Reflection

- Introduced to many new subjects
 - Quantum
 - Machine Learning
 - Cybersecurity at Ucy
- Learned much about the research process
 - Presenting findings
 - Writing IEEE style papers
 - Deliverables
- Had a fun and enriching cultural experience
- Satisfied, but want to iron out bugs



References

- [1] Rao, Sunil, et al. "Machine learning for solar array monitoring, optimization, and control." *Synthesis Lectures on Power Electronics* 7.1 (2020): 1-91.
- [2] Uehara, Glen S. "Quantum Machine learning using Quantum Simulators."
- [3] Rao, Sunil, Andreas Spanias, and Cihan Tepedelenlioglu. "Solar array fault detection using neural networks." *2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS)*. IEEE, 2019.
- [4] Uehara, Glen, et al. "Quantum Neural Network Parameter Estimation for Photovoltaic Fault Detection." *2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA)*. IEEE, 2021.