

QML FOR CONSPICUITY DETECTION

THE DETECTION DUOTEAM

- ML Engineer intern
- Graduated from physics major
- Currently Computer science undergraduate

- Full stack developer
- Currently pursuing phd in computer science
- Teaches university courses on optimization fundamentals, algorithmic techniques, and quantum algorithms

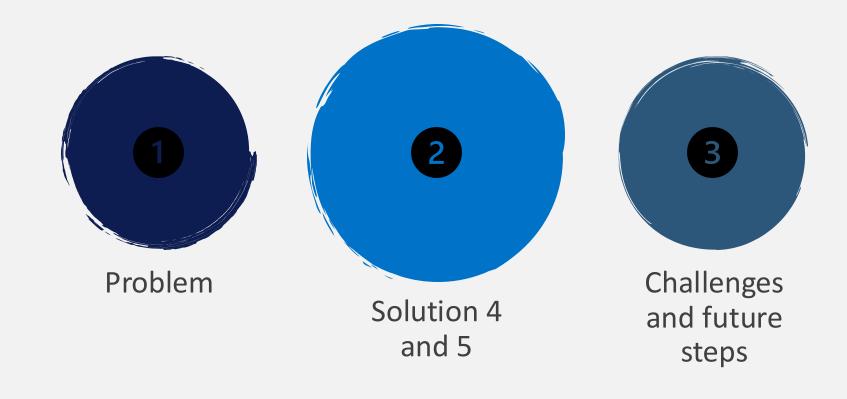




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Outline

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Problem

1

Predict sine function

• sin(x)

Predict more complicated sine function

• $2*\sin(x) + 0.7*\sin(3*x)$

2

Image classification

 Defective/nondefective

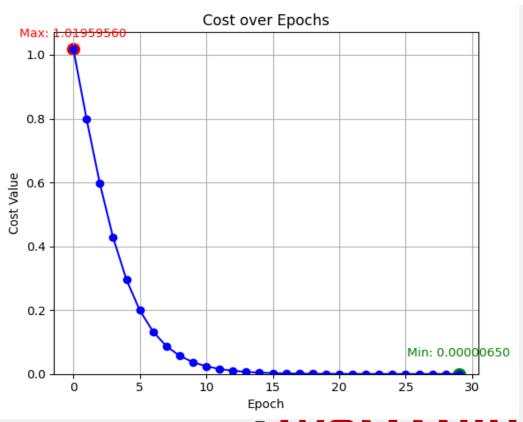
Find best accuracy

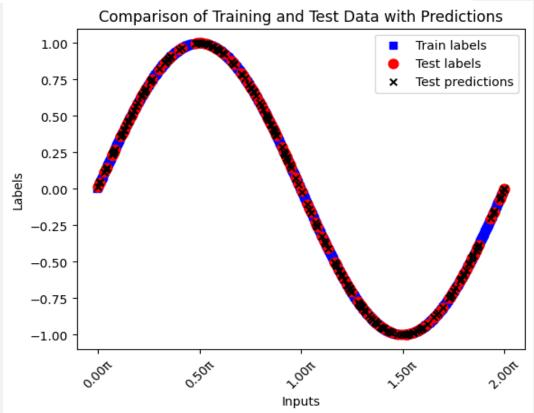
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Task 4 Solution part-1

Good Results for simple sine function but not for the complex one



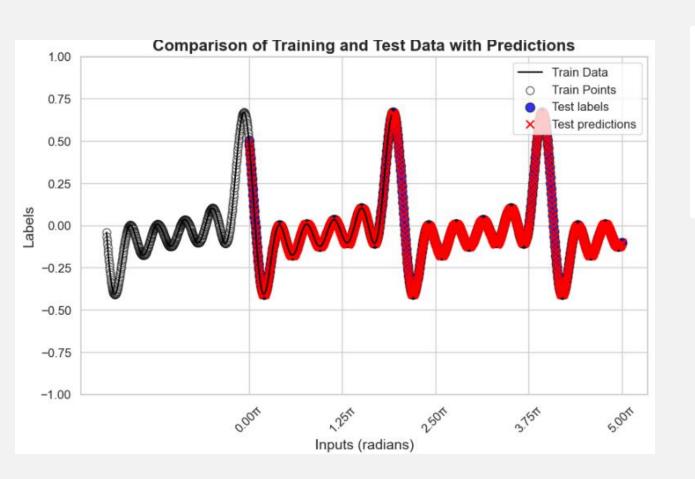


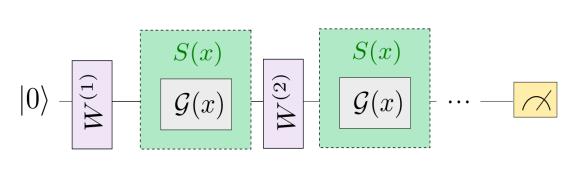


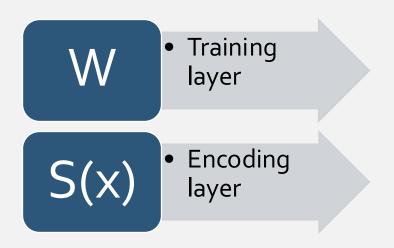
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Task4 Solution part-2

We used a different approach to account for low test accuracy in the complicated sine function:









Task 5 Approach 1 Images crop and resize Plot the confusion Dimensionality matrix and reduction using PCA calculate the F1score Train the model Find the loss comparing function that different loss gave the highest functions using accuracy 4 qubits. < WOMANIUM | QUANTUM >

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Task 5 Approach 1 COMANIUM | QUANTUM >

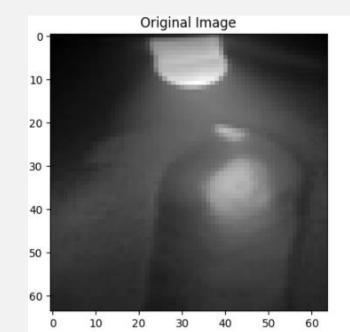


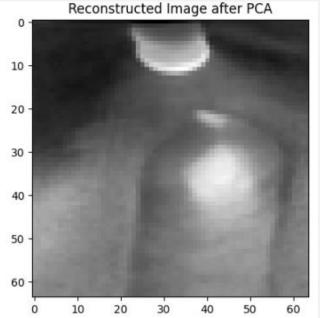
Crop and resize



PCA:

- Is a technique that can compress the image. So that we have fewer values to encode in our quantum circuit.
- The image can be decompressed after encoding or compressing, with minimal loss possible.





Task 5 Approach 2 Images crop and resize Plot the confusion Dimensionality reduction using matrix and Autoencoder. calculate the F1score Train the model Find the loss comparing function that different loss gave the highest functions using accuracy 8 qubits. **WOMANIUM** | QUANTUM >

Results for task 5 **WOMANIUM QUANTUM >**

Best results achieved:

92.67%

89.83%

Validation Accuracy

Test Accuracy

FL: Focal Loss

BCE: Binary Cross Entropy

Exponential Loss

8 Qubits

Exponential loss

Autoencoder

$$FL(p_t) = -(1-p_t)^\gamma \log(p_t)$$

$$Loss = -\sum_{i=1}^{ ext{output size}} y_i \cdot \log \hat{y}_i$$

$$loss = \sum_{i} (1 + 10e^{7p_i})^{-1}$$

Challenges and future scope

Trying to Challenges Computational Big images implement a dimensions resources novel approach Future Comparing with Extending for Find potential other models multiclassification speedup scope



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- [1] Esther Cruz Carlos A. Riofro Johannes Klepsch Juan Miguel Arrazola Diego Guala, Shaoming Zhang. Practical overview of image classification with tensor-network quantum circuits. Nature Journal, (12):1–12, 3 2023.
- [2] Frank Kster Hans-Martin Rieser and Arne Peter Raulf. Tensor networks for quantum machine learning. Royal Society, pages 1–23, 7 2023.
- [3] Patrick Holzer and Ivica Turkalj. Spectral invariance and maximality properties of the frequency spectrum of quantum neural networks. Physical Review A, 104(3):032404, 2021.
- [4] Enrico Prati Marco Lazzarin, Davide Emilio Galli. Multi-class quantum classifiers with tensor network circuits for quantum phase recognition. Arxiv, pages 1–7, 7 2021.
- [5] Mikko Mottonen, Juha J. Vartiainen, Ville Bergholm, and Martti M. Salomaa. Transformation of quantum states using uniformly controlled rotations. arXiv preprint quant-ph/0407010, 2004.
- [6] Maria Schuld, Alex Bocharov, Krysta Svore, and Nathan Wiebe. Circuit-centric quantum classifiers. Physical Review A, 101(3):032308, 2020.
- [7] Maria Schuld and Francesco Petruccione. Machine Learning with Quantum Computers. Springer International Publishing, 2019.
- [8] Maria Schuld, Ryan Sweke, and Johannes Jakob Meyer. The effect of data encoding on the expressive power of varia-tional quantum machine learning models. Physical Review A, 103(3):032430, 2021.

References:

THANKYOU

https://github.com/Martyna94/The_Detection_Duo %