Quantum Machine Learning for Earth Observation Images

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QUANTUM TECHNOLOGY INITIATIVE

Introduction

Quantum Machine Learning (QML)

- Intersection between Machine Learning (ML) and Quantum Computing (QC)
- Potential to **improve the existing ML techniques**
- Can be efficiently simulated on the real quantum hardware
- **Application of QML on images** still challenging

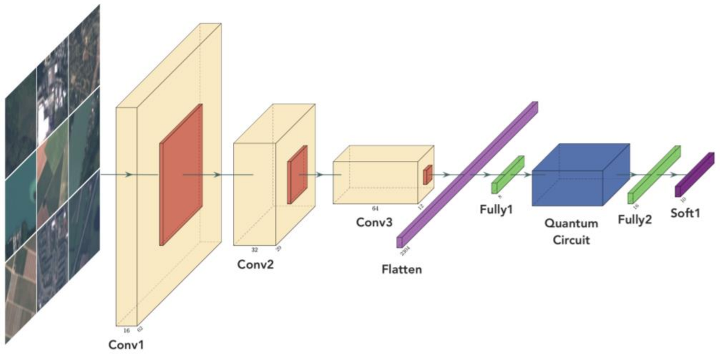
→ Large input dimensionality, quantum embedding methods

→ Limited to standard dataset (MNIST, Fashion MNIST, etc) [1]

Introduction

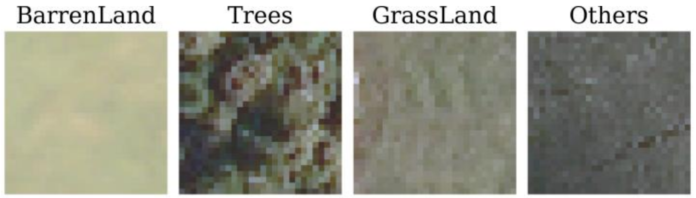
Earth observation images

- Highly benefit from ML
- Complex, unlabelled dataset with large number of features
- Increasing number of studies on QML applied on EO
- Explore **practical QML models** for a realistic EO use-case



Application of QML in EO [2]

EuroSAT image samples [3]



SAT4 image samples [4]

Classification of images

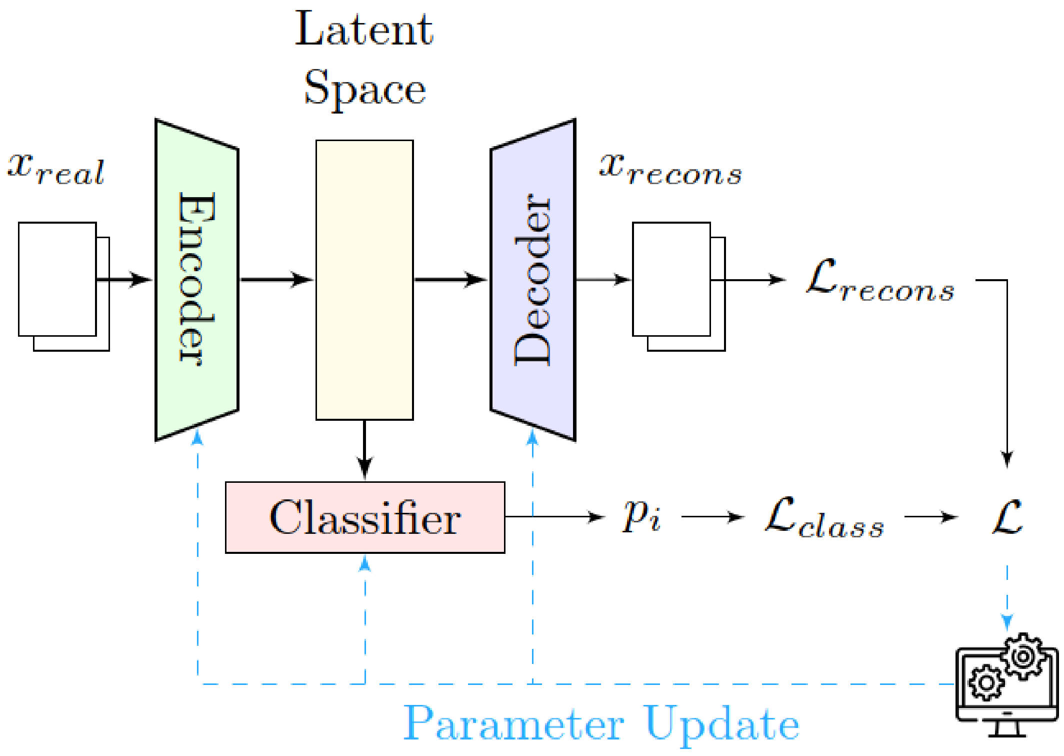
Hybrid Quantum-Classical model

- Multiclass-classification of large images
- Perform reconstruction & classification at the same time

→ Combine feature extractions & classification

- Latent space constrained in $[0, \pi]$
- Autoencoder = Classical

  Classifier = Classical / Quantum



Training schema of the hybrid model

Quantum Embedding

- Mapping of classical data x into quantum state $|\phi(x)\rangle$ in Hilbert space
- Crucial for the performance of quantum algorithm

Exponential compression in n_{qubits}, but polynomial n_{gates}

1) Amplitude Encoding

$$|\phi(x)\rangle = \frac{1}{\|x\|}\sum_{i=0}^{N-1} x_i |i\rangle$$

Constant n_{gates}, but no exponential compression

2) Dense Qubit Encoding

$$|\phi(x)\rangle = \bigotimes_{j=1}^{\frac{N}{2}} \left(e^{-i\frac{x_{\frac{N}{2}+j}}{2}\sigma_x} e^{-i\frac{x_j}{2}\sigma_y}\right)$$

Compromise between amplitude encoding and qubit encoding

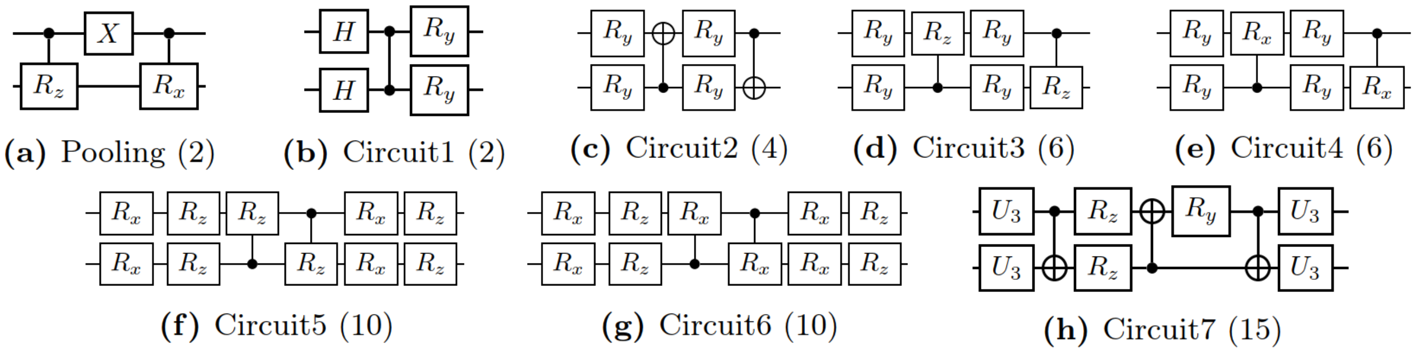
3) Hybrid Angle Encoding (HAE) [5]

$$|\phi(x)\rangle = \bigotimes_{k=1}^{b} \left(\sum_{i=1}^{2^m} \prod_{j=0}^{m-1} \cos^{1-i_j}(x_{g(j),k}) \sin^{i_j}\left(x_{g(j),k}\right)|i\rangle_k\right)$$

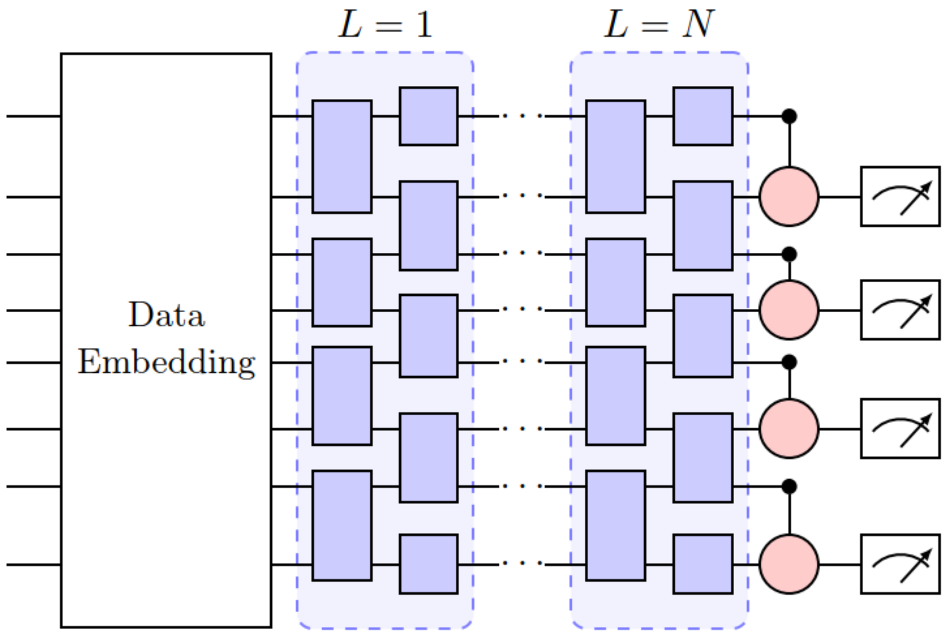
Quantum Convolutional Neural Networks

- Quantum analogue of CNN → Preserve translational invariance
- Avoid barren plateau problem
- Start with the model proposed by T. Hur et al. [5]
- Consists of convolutional filters & pooling layers

→ Different Ansatz to be investigated



PQC ansatzes used as convolutional filters [4]

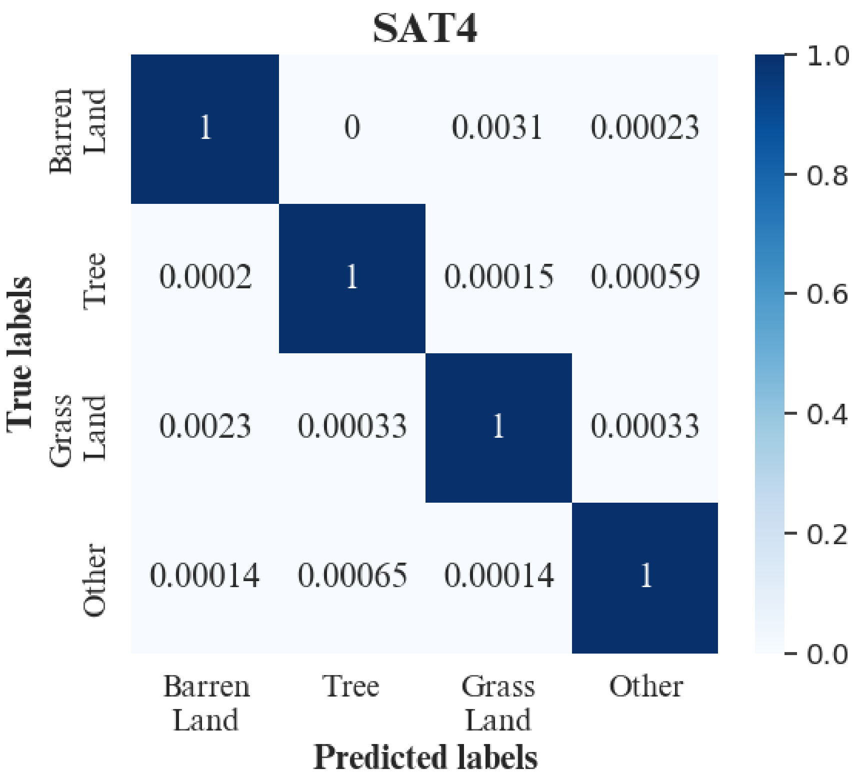


QCNN for multiclass-classification

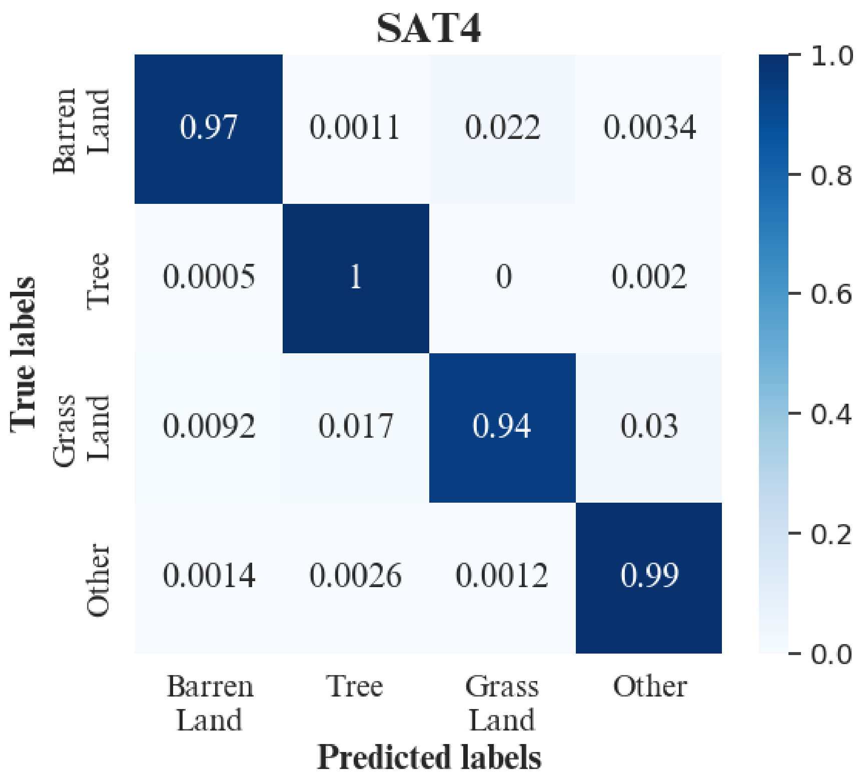
Results

- Train the hybrid model with <u>Circuit7 & L = 2</u> for **SAT4** (4 classes)

Training set



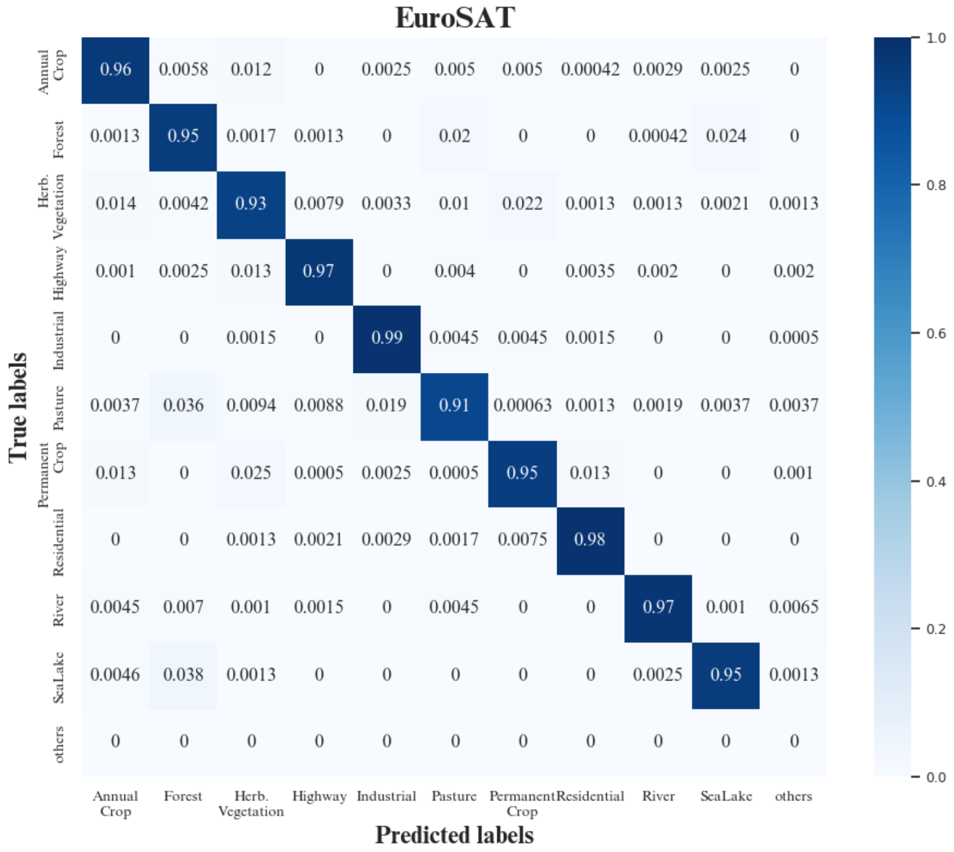
Test set



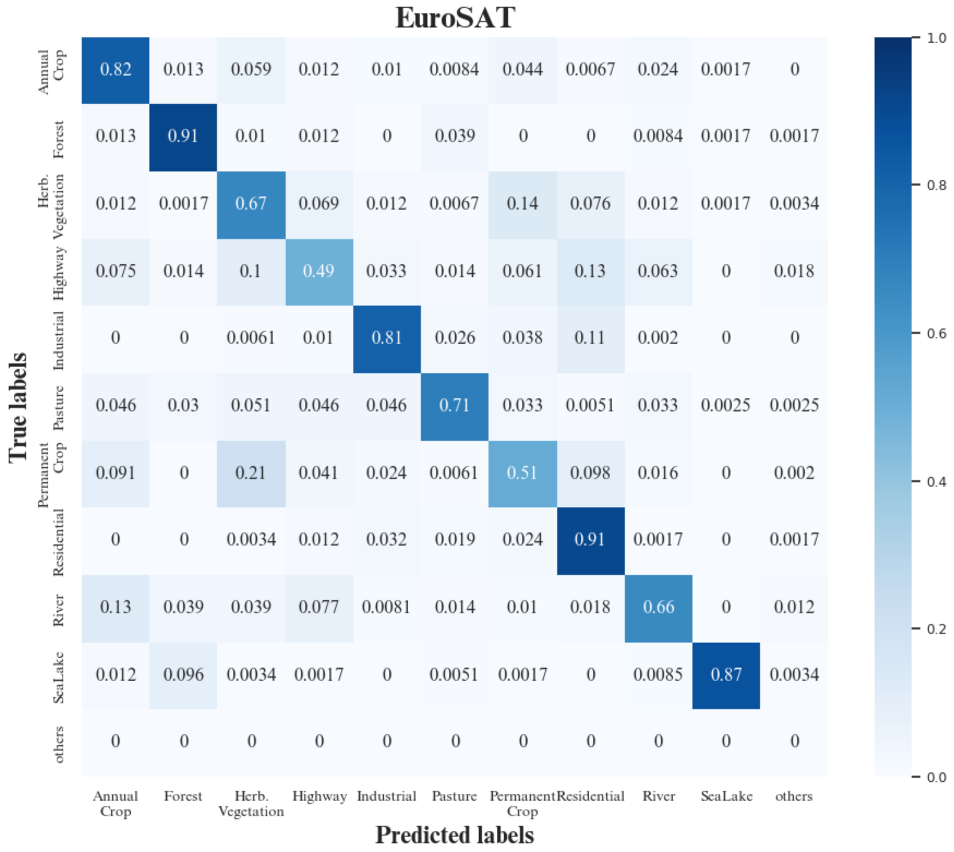
Results

- Train the hybrid model with Circuit7 & L = 1 for **EuroSAT** (10 classes)

Training set

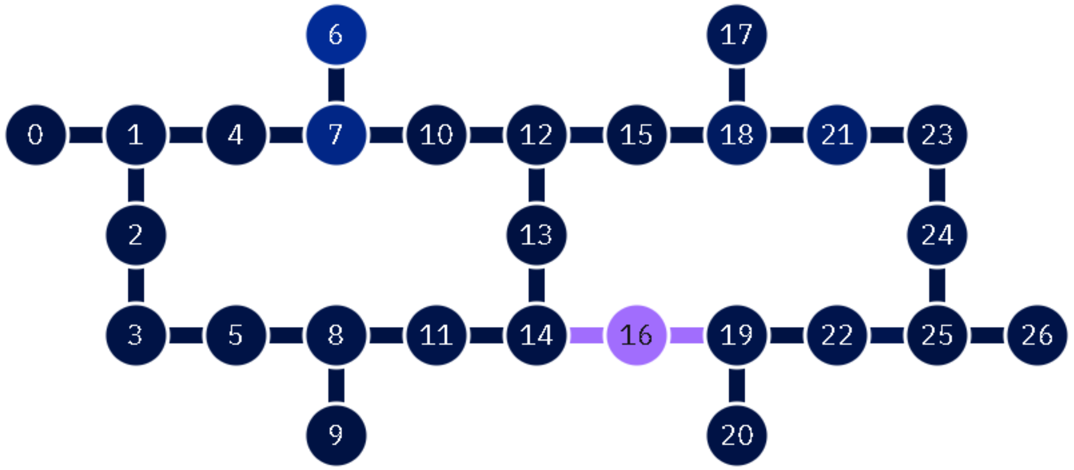


Test set

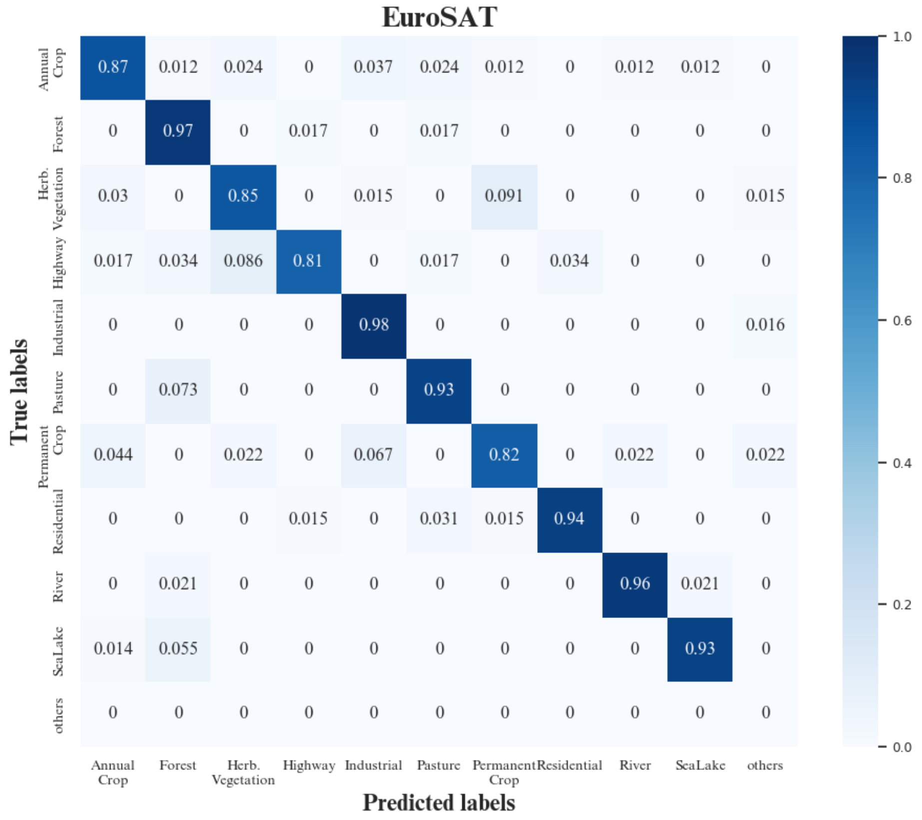


Results – Evaluation on real quantum hardware

- Evaluate pretrained model on IBMQ Montreal with 600 training samples



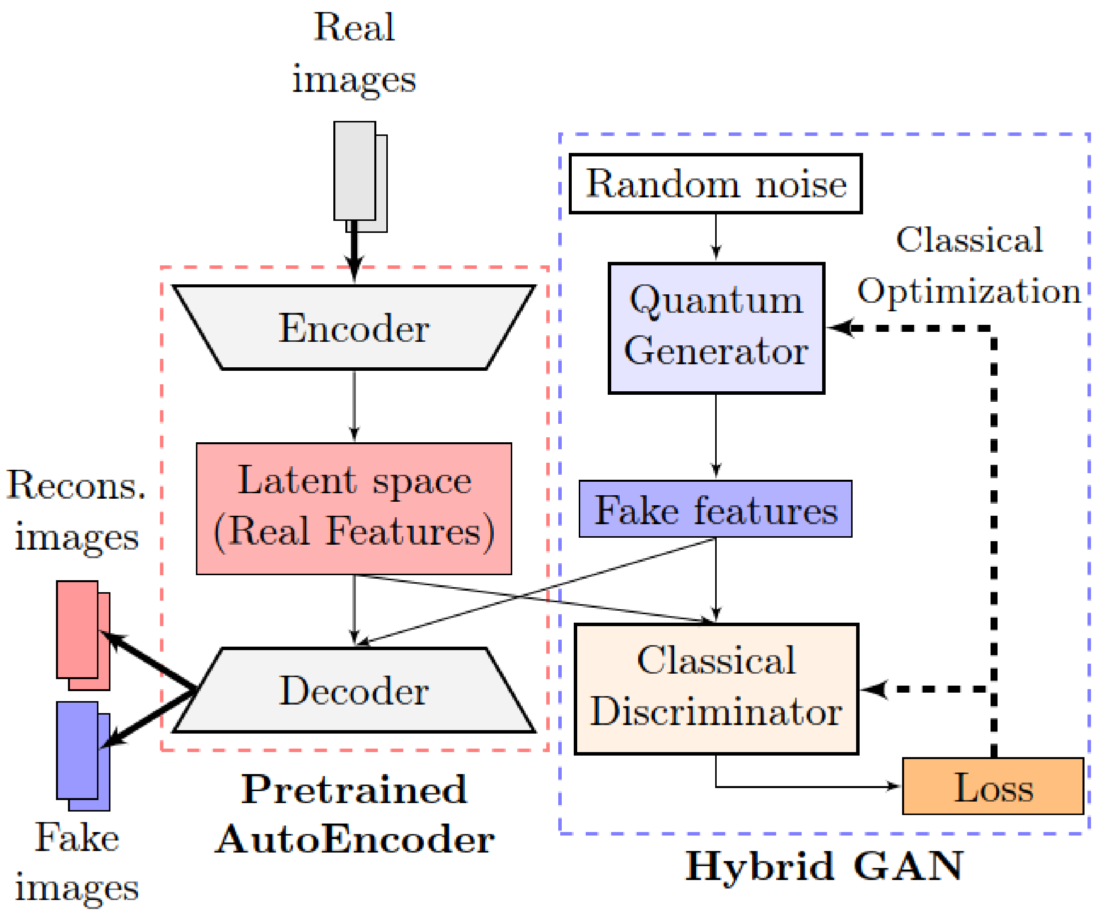
DQE + Circuit 3 (91% w/o noise)



Generation of images

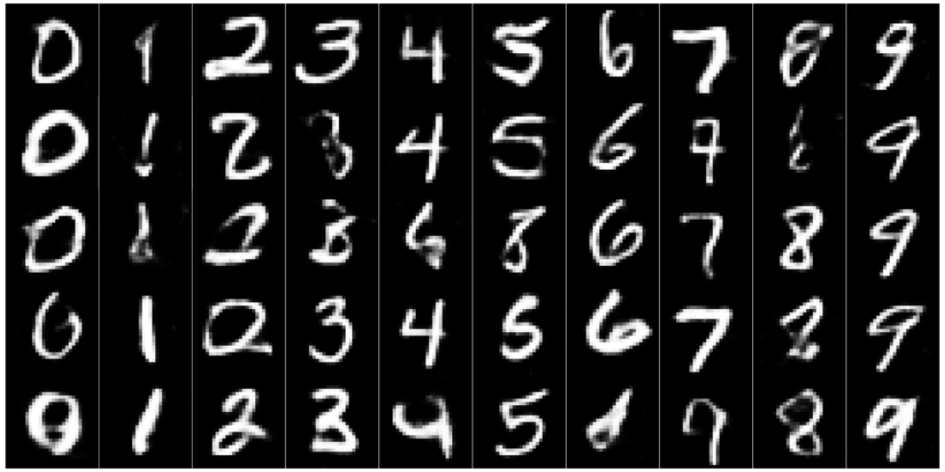
Hybrid Approach for image generation

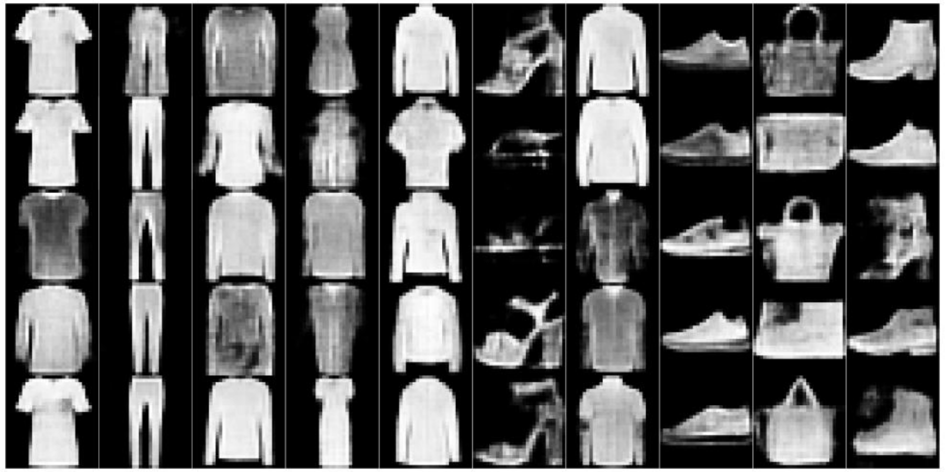
- Quantum Generative Adversarial Networks : **Quantum Generator + Classical Discriminator**
- Features extracted from images via a **pretrained autoencoder** used as GAN training set
- Generated features passed back to the autoencoder to reconstruct images



Training schema of the hybrid GAN

Results





Results

Quality | Diversity

	G_{θ} config.	# param.	FID ↓	IS ↑	JSD (features/10^{-2}) ↓	JSD (images/10^{-2}) ↓
LaSt-QGAN	Circ. 1 ($d=2$)	1360	17.89 ± 0.57	8.21 ± 0.05	1.00 ± 0.15	1.75 ± 0.2
	Circ. 1 ($d=4$)	2280	15.04 ± 0.49	8.47 ± 0.05	1.00 ± 0.10	1.62 ± 0.15
	Circ. 1 ($d=6$)	3200	$\mathbf{14.34 \pm 0.41}$	$\mathbf{8.47 \pm 0.03}$	0.87 ± 0.09	$\mathbf{1.37 \pm 0.14}$
	Circ. 2 ($d=2$)	1010	19.13 ± 0.54	8.10 ± 0.06	1.22 ± 0.19	2.08 ± 0.17
	Circ. 2 ($d=4$)	1690	16.2 ± 0.32	8.34 ± 0.03	0.94 ± 0.09	1.66 ± 0.17
	Circ. 2 ($d=6$)	2370	14.85 ± 0.61	8.47 ± 0.06	$\mathbf{0.85 \pm 0.05}$	1.39 ± 0.11
	Circ. 3 ($d=2$)	3300	14.54 ± 0.50	8.48 ± 0.05	1.01 ± 0.2	1.54 ± 0.1
Classical	[50, 30]	2960	19.41 ± 3.78	8.12 ± 0.36	5.78 ± 3.33	5.71 ± 3.19
	[100, 50]	7660	13.21 ± 0.94	8.72 ± 0.06	1.73 ± 0.44	1.89 ± 0.37

Conclusion

- Hybrid quantum-classical model for EO image classification

→ Successful multi-class classification (99% for training, >75% for test)

- Two-step approach for generation of images

→ Higher generalization power compared to the classical counterpart

Would it be possible to define the quantum advantage in a more solid way?

QUESTIONS?

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References

[1] Hubregtsen, T., Pichlmeier, J., Stecher, P. et al. (2021) Evaluation of parameterized quantum circuits: on the relation between classification accuracy, expressibility, and entangling capability. Quantum Mach. Intell. 3, 9.

[2] Sebastianelli, A., Zaidenberg, D., Spiller, D., Saux, B., & Ullo, S. (2022). On Circuit-Based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 15, 565-580.*

[3] Helber, P., Bischke, B., Dengel, A., & Borth, D. (2018). Introducing Eurosat: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification. *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, 204-207.

[4] Basu, S., Ganguly, S., Mukhopadhyay, S., Dibiano, R., Karki, M., and Nemani, R., DeepSat - A Learning framework for Satellite Imagery, ACM SIGSPATIAL 2015.

[5] Hur, T., Kim, L., & Park, D.K., (2021). Quantum convolutional neural network for classical data classification.