Hybrid Quantum-Classical Networks for Reconstruction and Classification of EO Images

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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

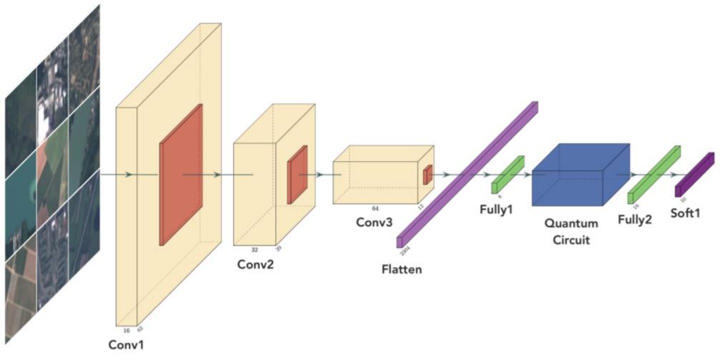
- Further understanding required to understand relation between quantum circuit architecture & training performance

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

Introduction

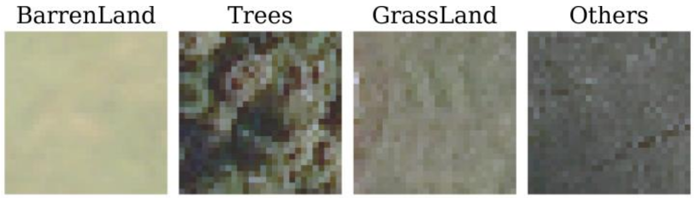
Earth observation images

- Highly benefit from ML
  - Complex, unlabelled dataset with large number of features
  - Increasing number of studies on QML applied on EO
- Evaluate **the correlation between training performance and quantum circuit architecture** for a realistic EO use-case



Application of QML in EO [2]

EuroSAT image samples [3]



SAT4 image samples [4]

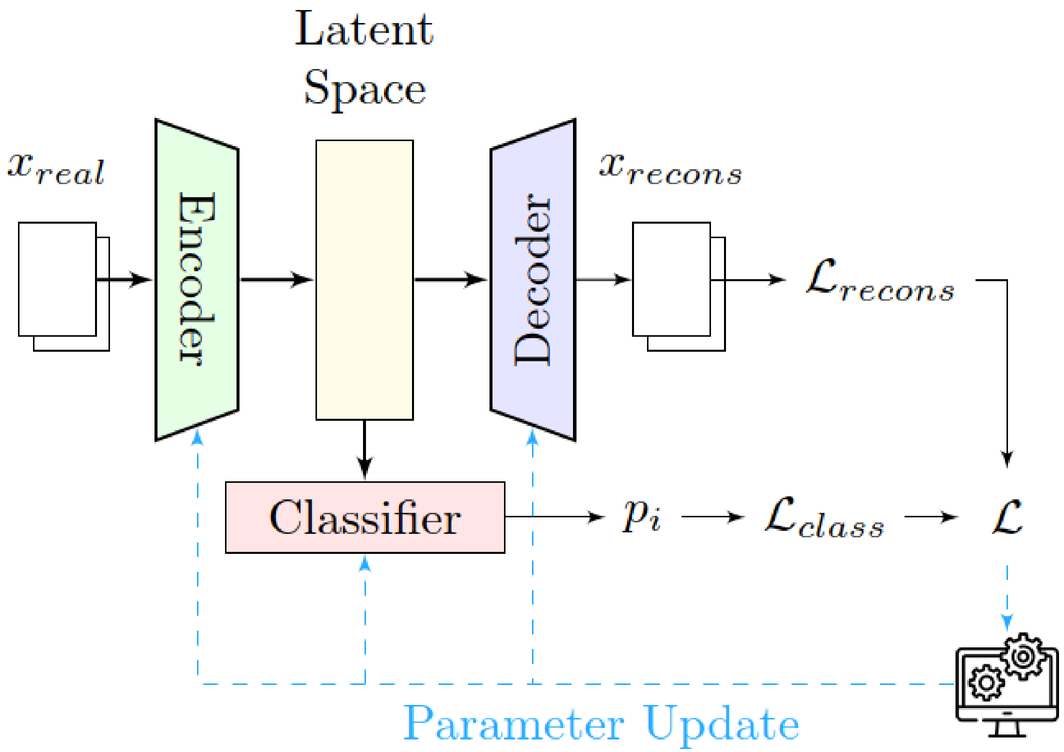
Hybrid Quantum-Classical model

- 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**

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

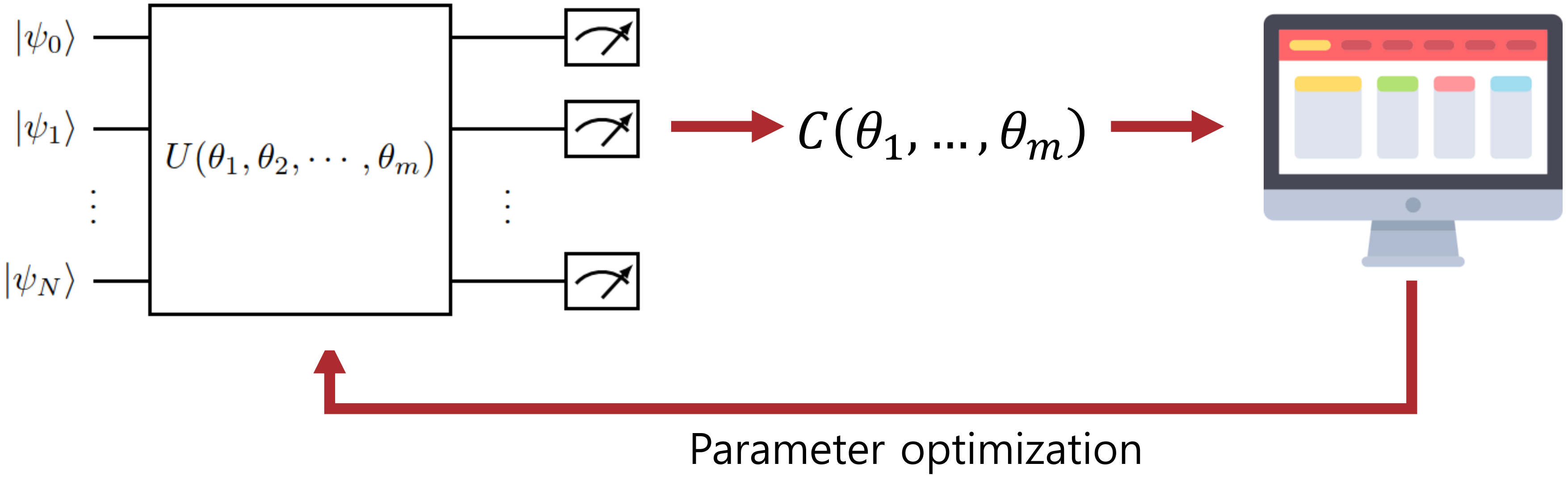
3) **Hybrid Angle Encoding (HAE) [4]**

Compromise between amplitude encoding and qubit encoding

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

Parameterized Quantum Circuit (PQC)

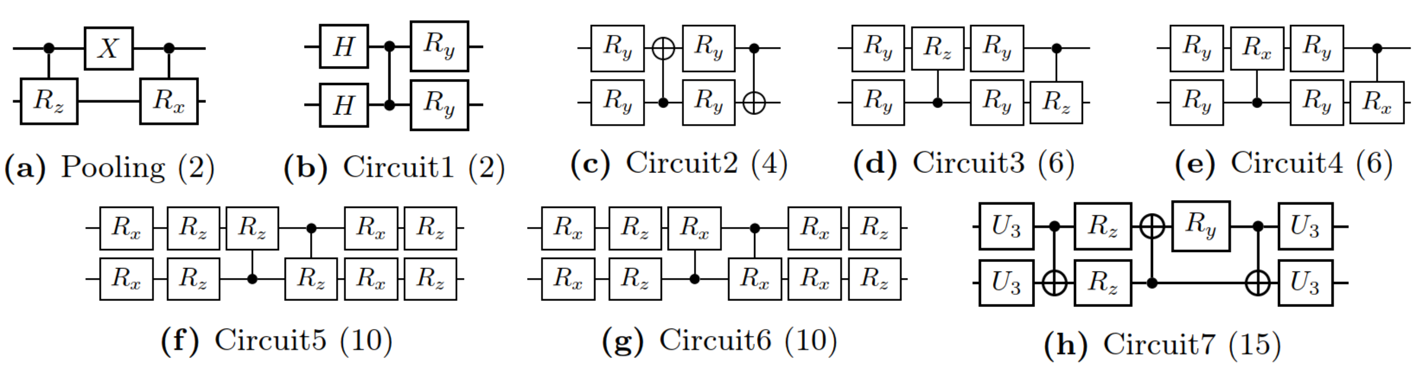
- Quantum analogue of Neural Networks
- Rotation angles = Free parameters
- Tune the parameters classically
- Framework to solve a variety of problems
- Challenges : Trainability, accuracy and efficiency



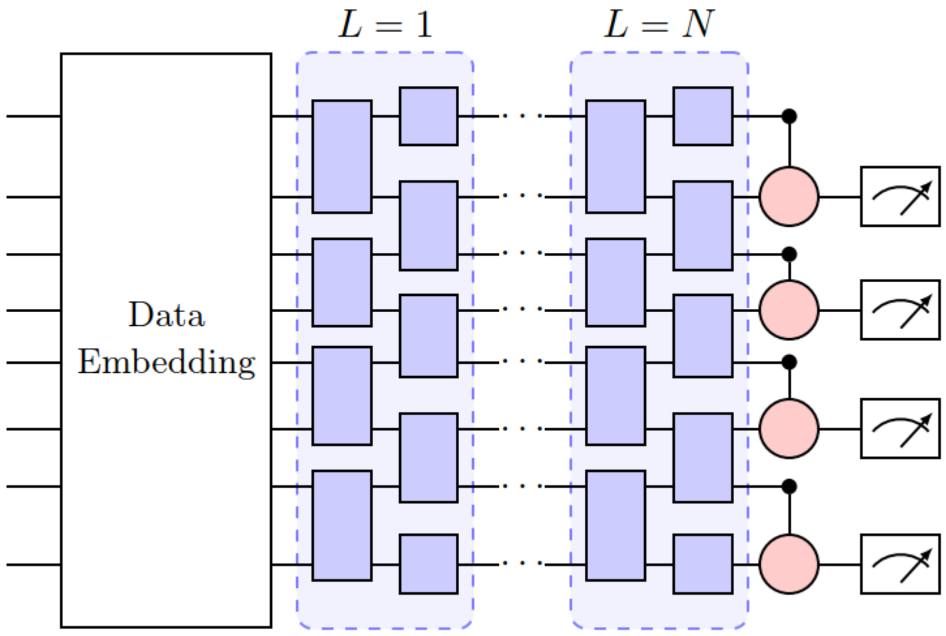
Quantum Convolutional Neural Networks

- Quantum analogue of CNN → Preserve translational invariance
- Avoid barren plateau problem
- Start with the model proposed by T. Hur et al. [4]
- Consists of convolutional filters & pooling layers

→ Different Ansatz to be investigated



PQC ansatzes used as convolutional filters [4]



QCNN for multiclass-classification

PQC Descriptors

- Metrics to measure the expressive power of a chosen PQC [1,5]
- **Expressibility** : Measure the capability of quantum circuit to express an arbitrary quantum state

$$Expr' = -\log_{10} D_{KL}(\hat{P}_{PQC}(F;\theta)||P_{Haar}(F))$$

- **Entangling Capability** : Capture the capability of a PQC to generate highly entangled states

$$Ent = \frac{1}{|S|}\sum_{\theta_i \in S} Q(|\psi_{\theta_i}\rangle)$$

S = Set of sampled circuit parameters

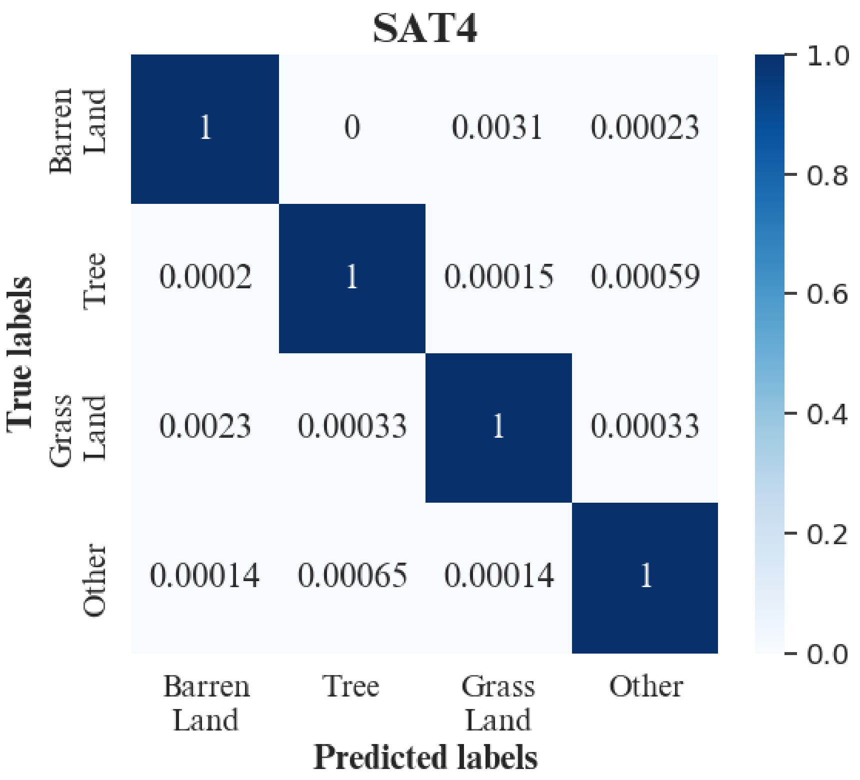
$Q(|\psi\rangle)$ = Meyer-Wallach entanglement measure

→ Investigate relation between PQC descriptors and training performance

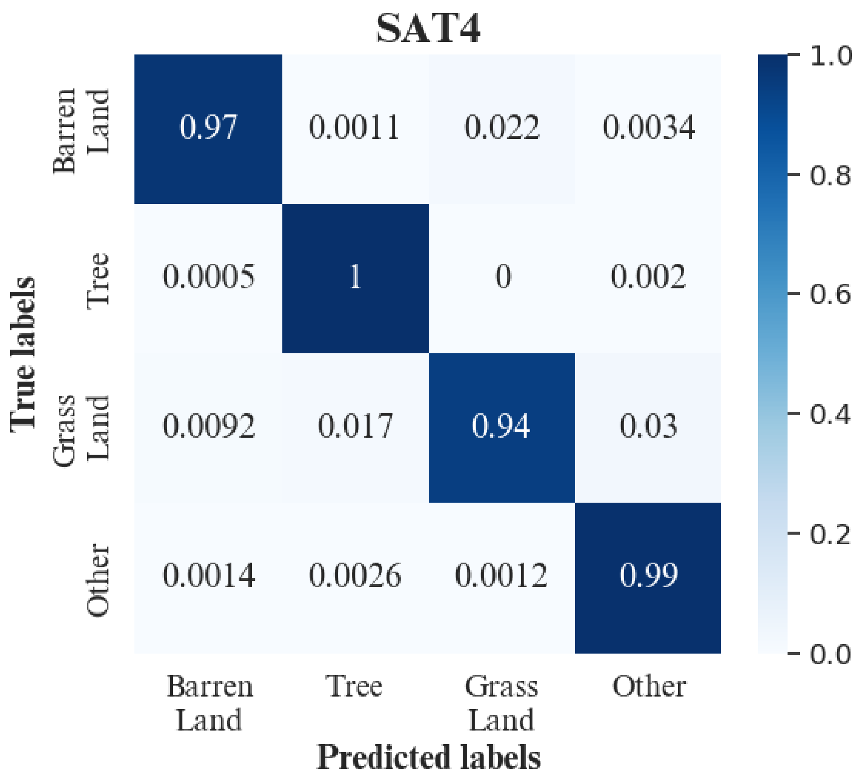
Results

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

Training set



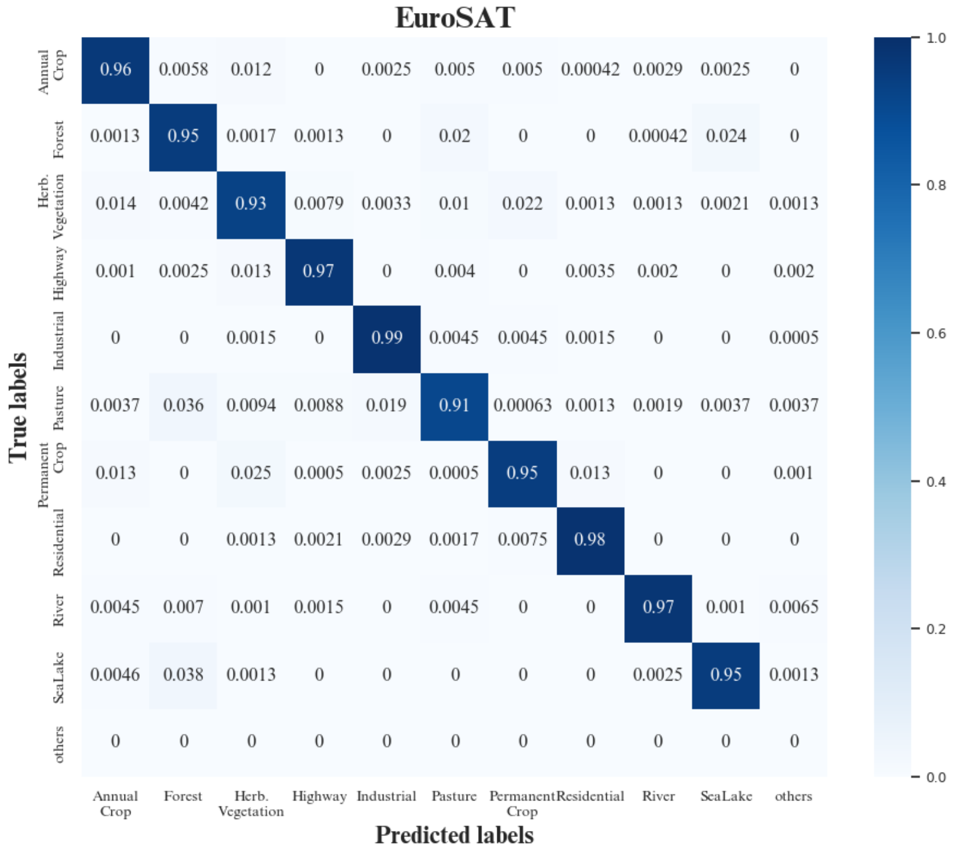
Test set



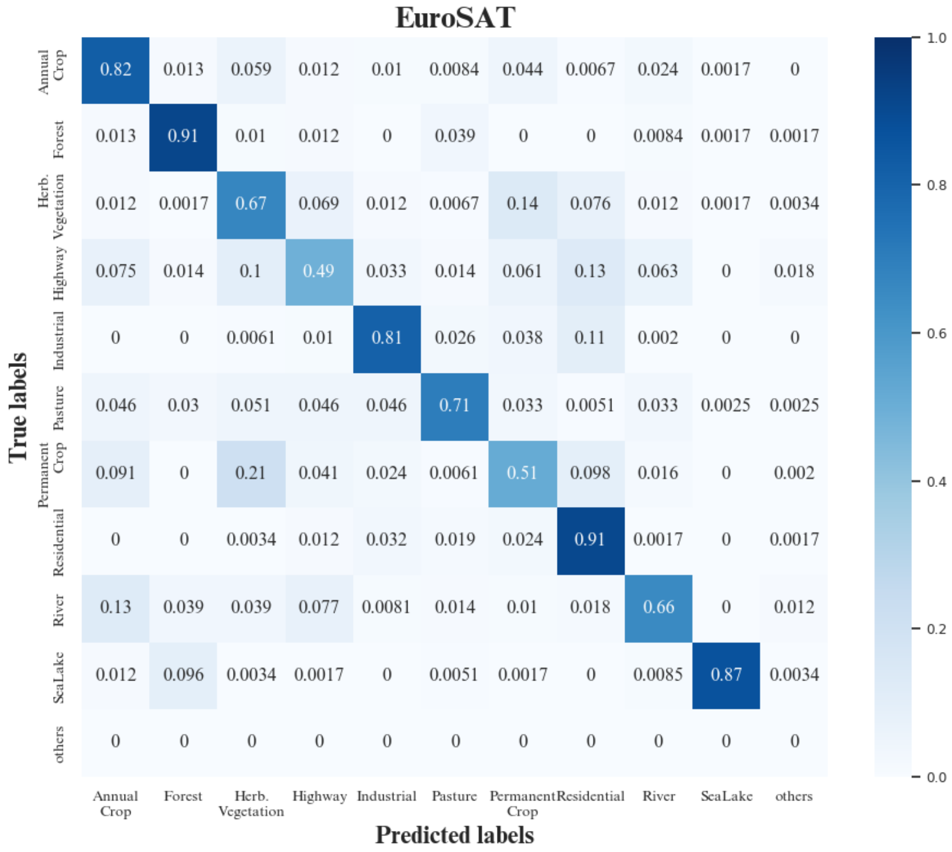
Results

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

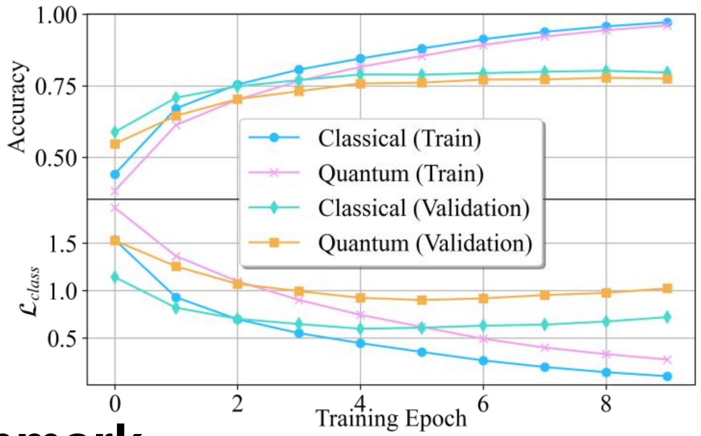
Training set

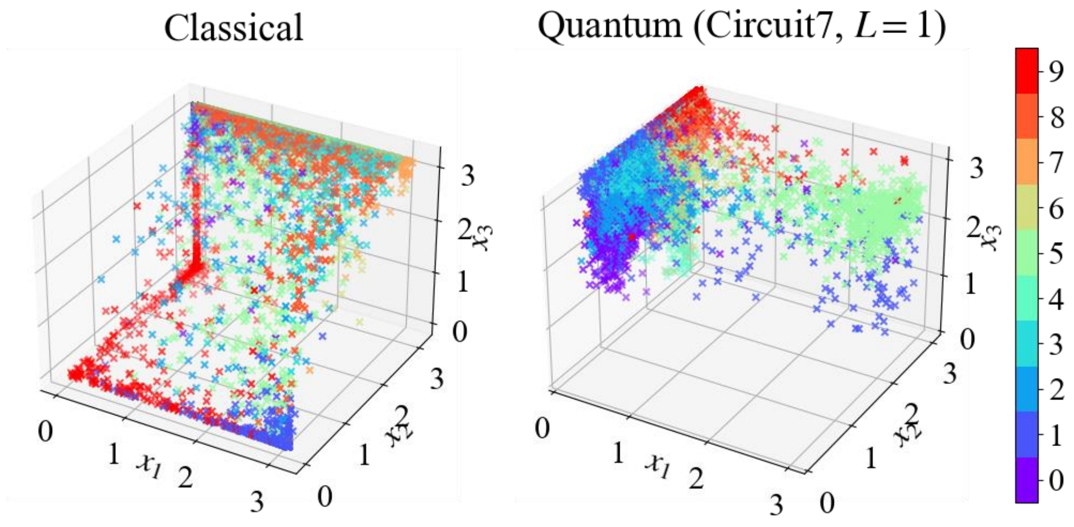


Test set

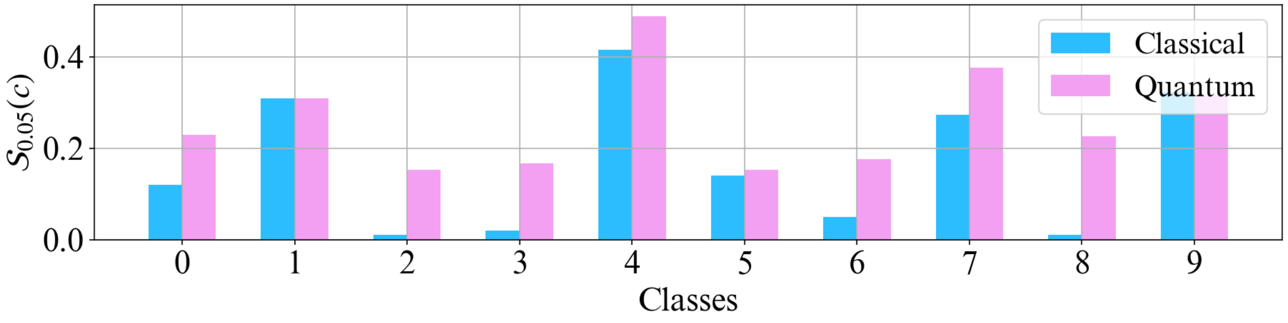


Results – Distribution of latent features





Distribution in the first 3 components of the latent features



Sparsity measure $S_\delta(c)$ with $\delta = 0.05$

Classical benchmark

- Classifier with 1D convolutional layer

- Natural emergence of sparse feature distribution

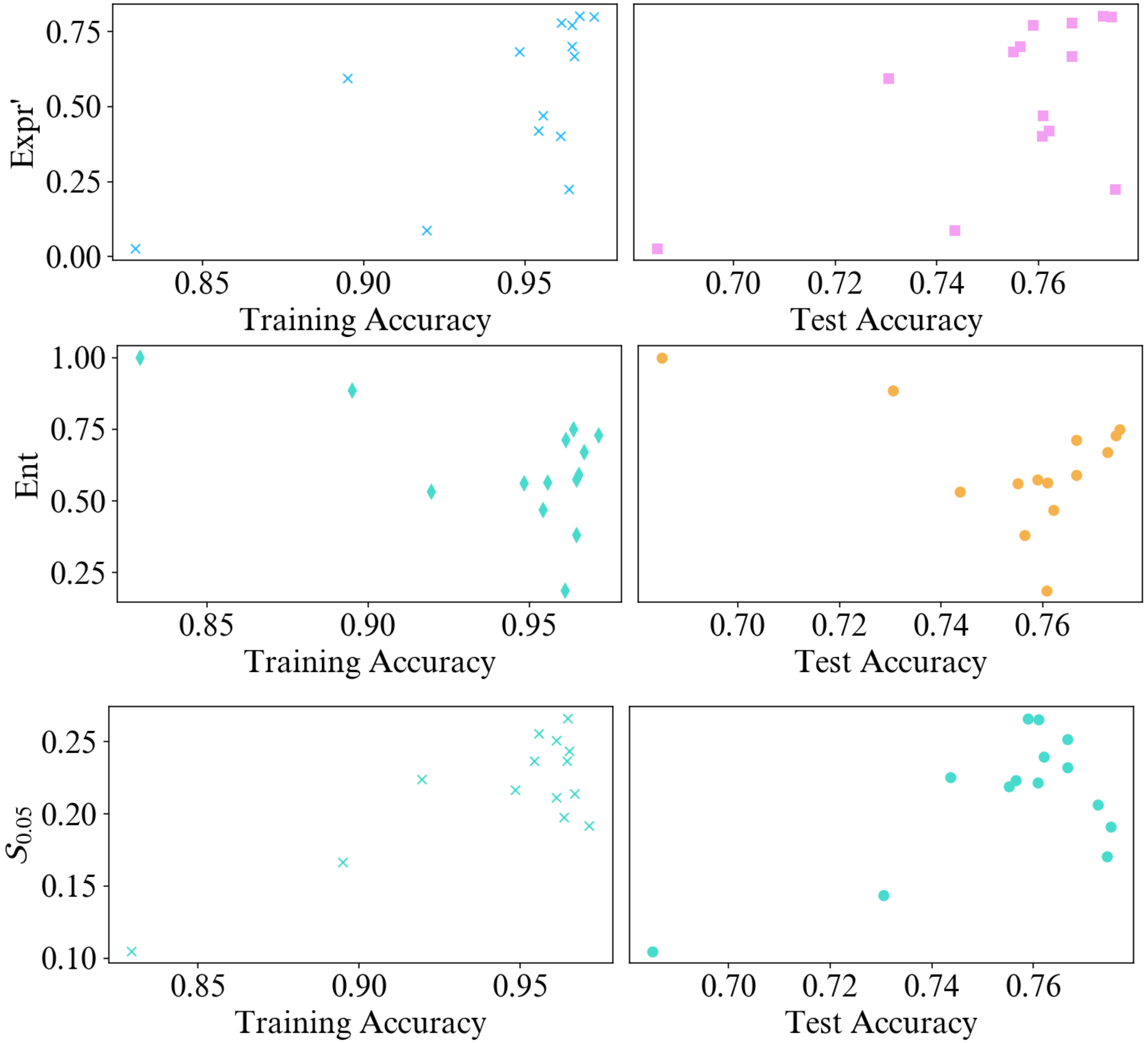
→ Measure sparseness of latent features

$$S_\delta(c) = \left|\{j \mid x_j(c) < \delta \text{ or } x_j(c) > \pi - \delta\}\right|$$

with $\bar{x}_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$

- $S_{\delta,classical} < S_{\delta,quantum}$

Results – Relation with PQC descriptors



- **Pearson Correlation Coefficient**

	Training	Test
Expr' v.s. Acc	0.63	0.57
Ent v.s. Acc	-0.60	-0.48
S_δ v.s. Acc	0.80	0.65

- Higher Expr' → Higher Accuracy
- Higher Ent → Lower Accuracy

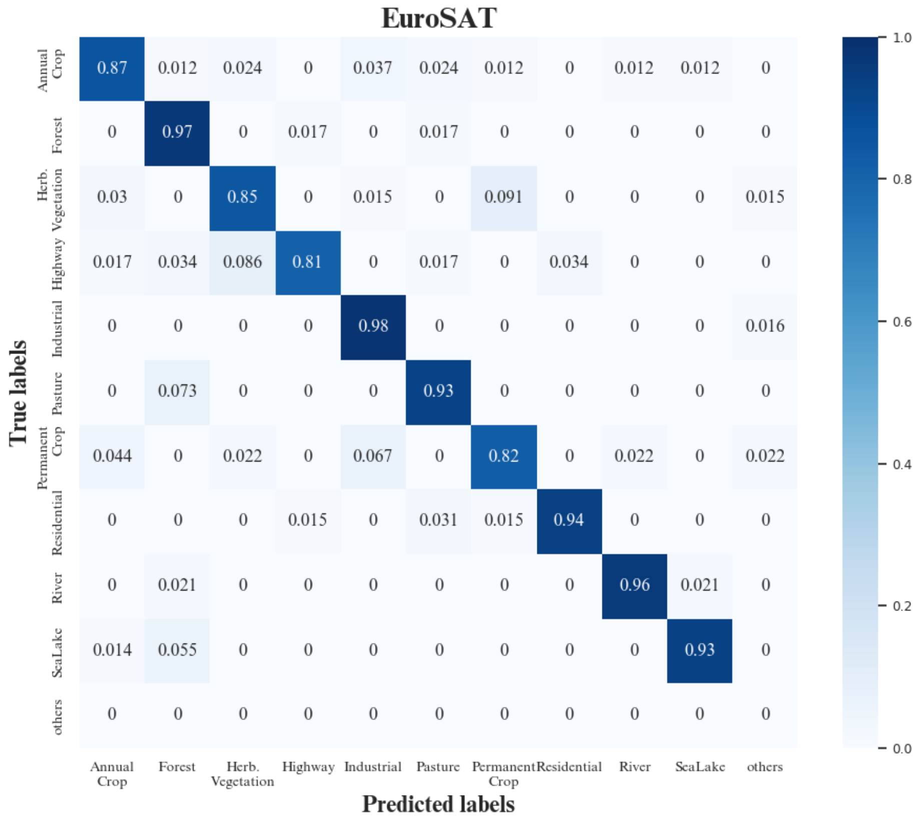
→ Possibility that entanglement hinders training

- Higher S_δ → Higher Accuracy

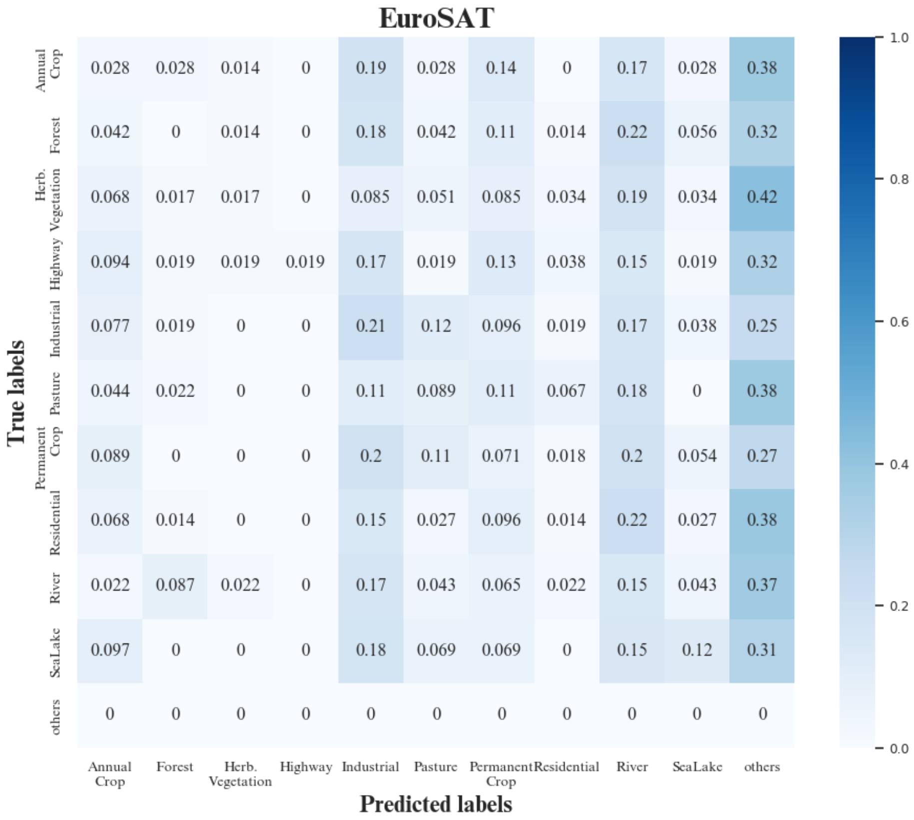
Results – Evaluation on real quantum hardware

- Evaluate pretrained model on IBMQ Montreal with 600 training samples

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



HAE + Circuit 3 (96% w/o noise)



Conclusion

- Construct hybrid quantum-classical model for EO image classification

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

- High correlation between PQC descriptors and the accuracy

→ Evidence of drawbacks for highly entangled states

- Paves the way to generic approaches for choosing the right ansatz for a given problem

Future plans

- **Solve overfitting problem & Improve reconstruction power**
- **Study other characteristics of PQC (convergence rate, optimization landscapes)**
- **Investigate a way to encode the data with complex correlation**

QUESTIONS?

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References

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[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.

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

[6] Sim, S., Johnson, P. D. & Aspuru-Guzik, A., (2019). Expressibility and entangling capability of parameterized quantum circuits for hybrid quantum-classical algorithms. *Advanced Quantum Technologies 2(12)*

[7] Ortiz Marrero, C., Kieferova, M., & Wiebe, N. (2021). Entanglement-Induced Barren Plateaus. *PRX Quantum, 2, 040316.*