QML FOR EARTH OBSERVATION IMAGES

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INTRODUCTION

- **Earth observation**: often train with partially or unlabelled dataset
  → Highly benefit from generative models, including Generative Adversarial Networks (GAN)
- On-going study on **Quantum Machine Learning** (QML) applied in Earth observation domain [1]

OBJECTIVES

- Inspired by Ref. [2], we test **Quantum Convolutional Neural Network** (QCNN) architecture on Earth observation images (EuroSAT dataset)
- Test QCNN as a binary classifier for real and fake data and as a multiclass classifier
- Based on the initial works, we ultimately aim to reproduce **unlabelled Earth observation images**s using quantum generative adversarial networks

QUANTUM EMBEDDING

To encode classical data x as a quantum state $|\psi(x)\rangle$, we use **Hybrid Angle Encoding** (HAE) [2] with b blocks of m qubits:

$$|\psi(x)\rangle = \bigotimes_{k=1}^{b} |\psi_k(x)\rangle \quad (1)$$

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

where $g(j) = 2^j + \sum_{\ell=0}^{j-1} i_\ell 2^\ell$ and $|i\rangle = |i_0 \cdots i_m\rangle$ with $i_j \in \{0, 1\}$.

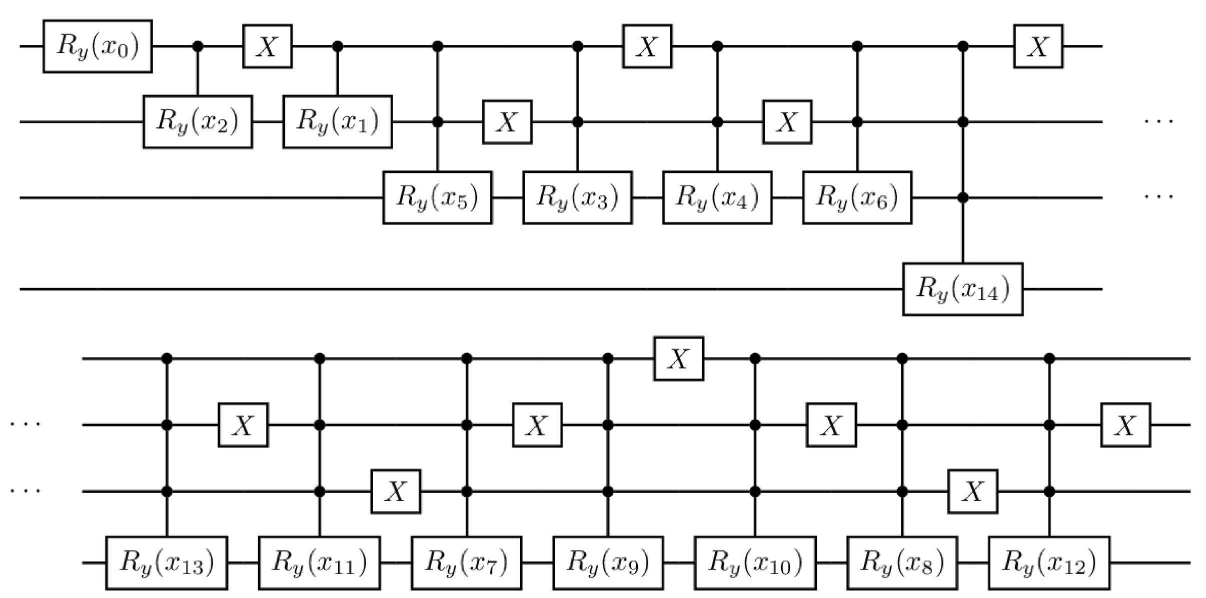


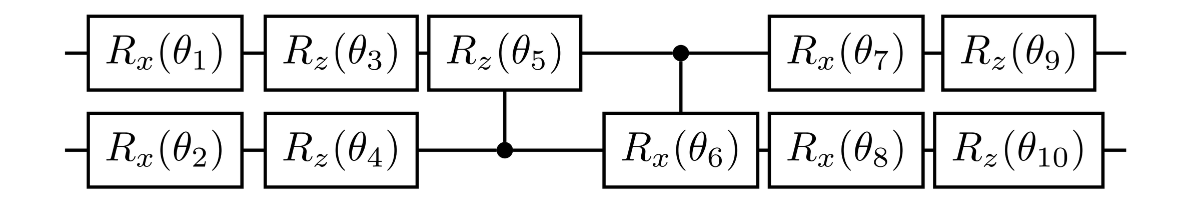
Figure 1: Quantum circuit to embed a classical data as a 4-qubits quantum state with the equation

Pros: 1. Able to get x back from the probability distribution (unlike dense qubit encoding). 2. Good qubit-gate compromise (between the two extremes of qubit and amplitude encodings)
Cons: Increase in circuit complexity (two-qubit gates number)

QUANTUM CNN

The convolutional circuits that we tested are taken from Ref. [2]

- Convolutional Filters - Parameterized Quantum Circuits (PQC) with single-qubit and two-qubit operations.



(a) U_6 (10 parameters)

(b) U_{SU4} (15 parameters)

Figure 2: Examples of convolutional filters used for the study. Further details could be found in Ref. [2]

- Pooling - PQC applied on two-qubits to reduce the two-qubit states to one-qubit states.

- Reduces the risk of **barren plateau**
- Version 1: Identical PQCs in a single layer → Translational invariance
- Version 2: Different parameters in each convolutional filters → increased model complexity and flexibility
- Study the influence of different gates on the model expressibility.

DIMENSIONALITY REDUCTION

- Impossibility of original image size encoding (EuroSAT: $64 \times 64 = 4096$ features) → **Extract features** using classical methods:
  1. PCA
  2. Convolutional Autoencoder (keeps spatial structure)
- For this study, we reduce the images to $N = 30$ features → QCNN with 2 blocks of 4 qubits

REFERENCES

[1] A. Sebastianelli et al. On circuit-based hybrid quantum neural networks for remote sensing imagery classification, 2021.

[2] T. Hur, L. Kim, and D. K. Park. Quantum convolutional neural network for classical data classification, 2021.

BINARY CLASSIFICATION

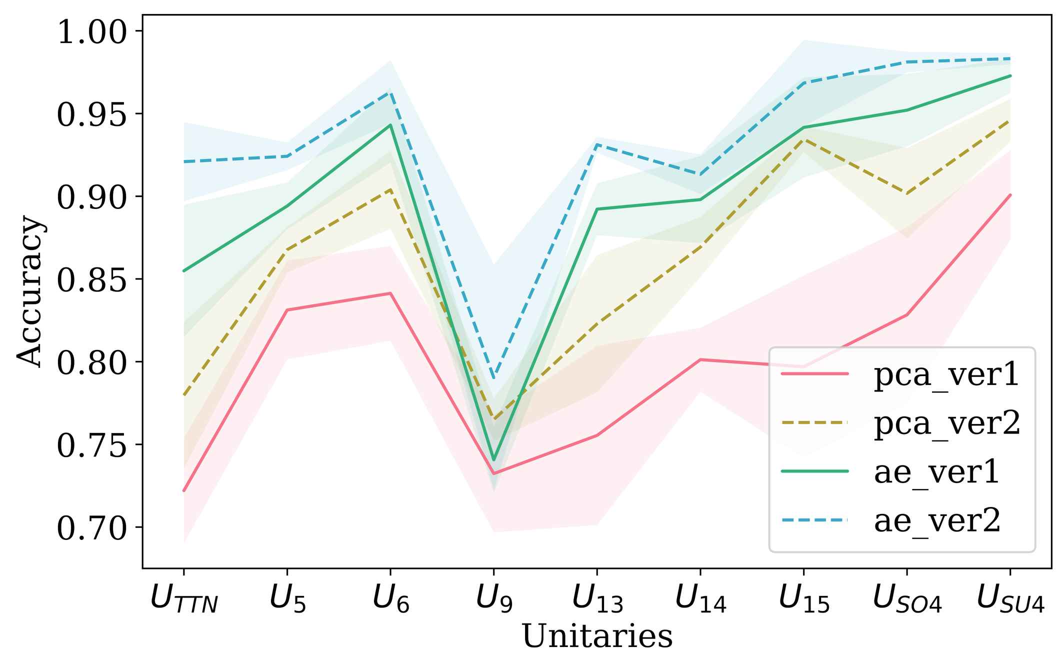


Figure 3: Influence of the choice of gates for a real-fake classification task on the EuroSAT dataset. The fake dataset is created by sampling randomly from a uniform distribution.

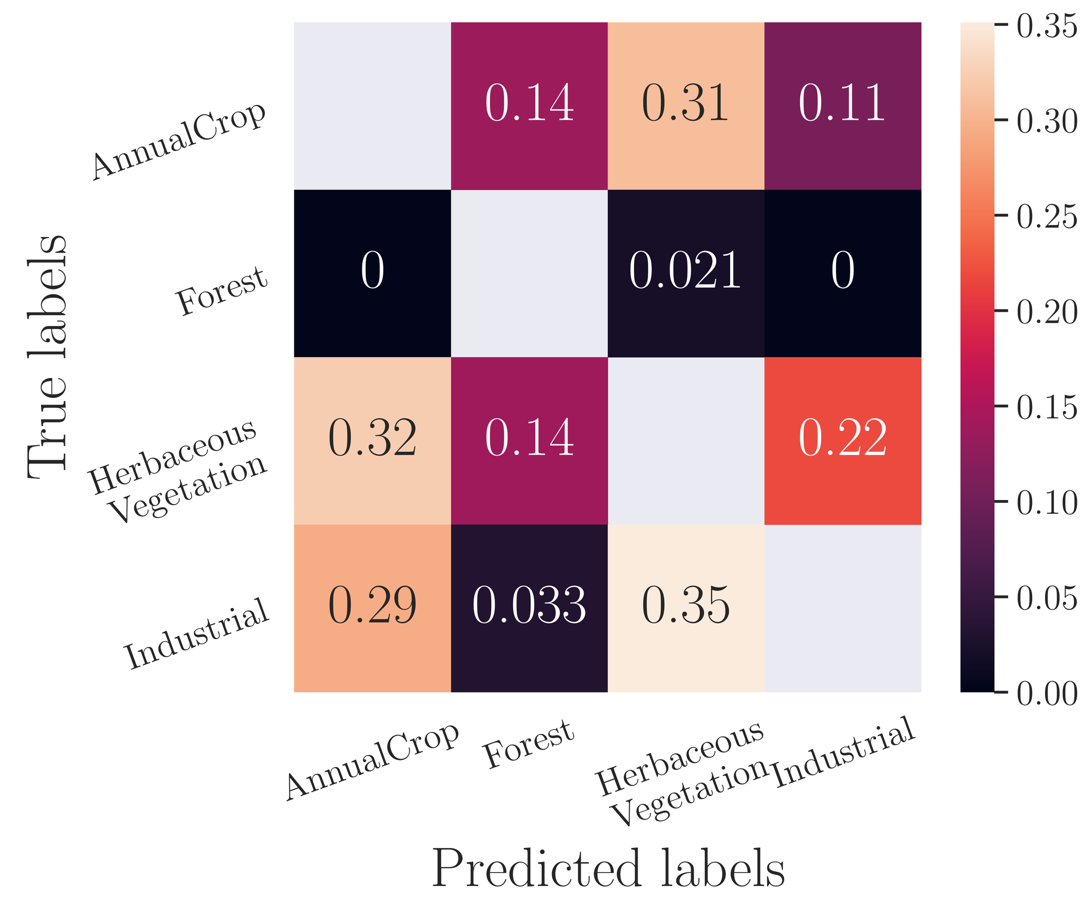


Figure 4: Confusion matrix obtained by binary classifications using PCA and U_6 circuit. The classification is performed by taking successively couples of classes among 4 classes.

DISCUSSION

- High Accuracy of real-fake binary classification
  → Best result with **version2 + autoencoder**
  → Possibility to use QCNN as a discriminator in quantum GAN
- Accuracy of binary classification varies depending on the classes (50%∼97%)
- High accuracy for multiclass classification of MNIST dataset (except for class 2), but more simulations and studys are required for EuroSAT dataset

MULTICLASS

- We perform **L-class classification** by measuring the probability distribution for $\log_2(L)$ qubit and using categorical cross entropy.

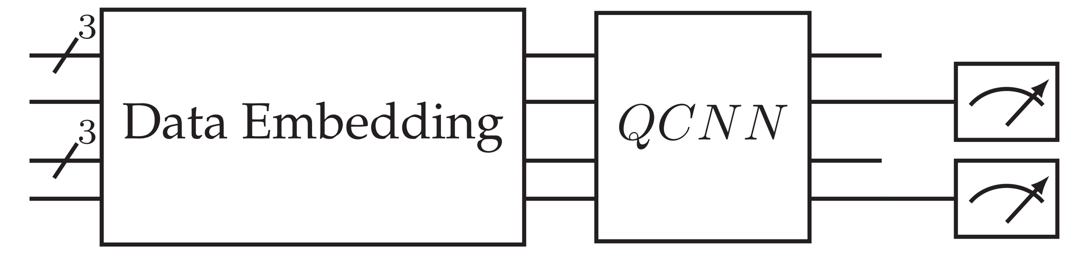


Figure 5: Schematic diagram of quantum circuit for four-class classification.

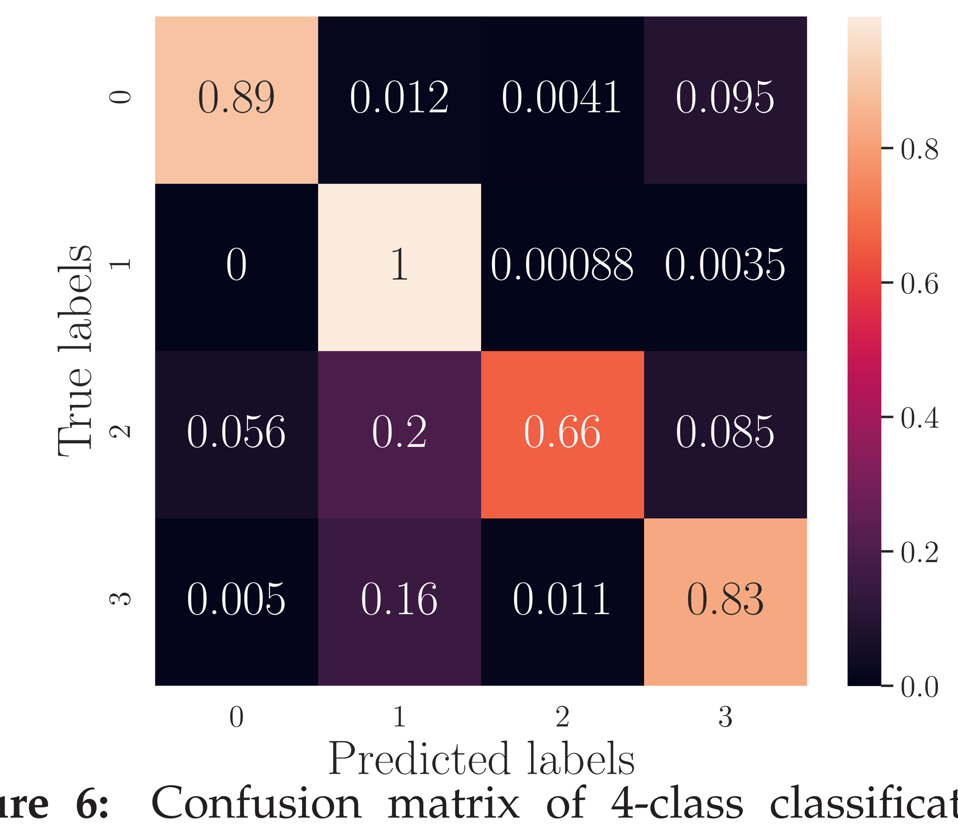


Figure 6: Confusion matrix of 4-class classification for MNIST dataset with U_6 circuit.

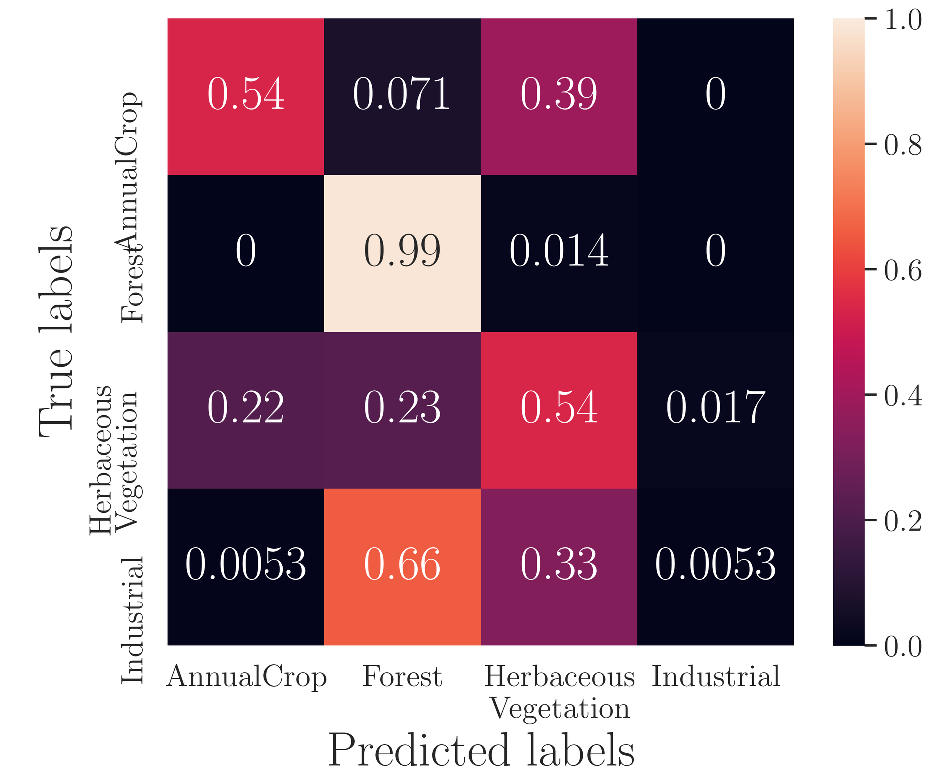


Figure 7: Confusion matrix of 4-class classification of EuroSAT dataset with U_6 circuit.

ONGOING RESEARCH

We are planning to increase the input feature size and investigate other feature extraction methods and convolution filters to improve the classification accuracy. Ultimately, we aim to **use QCNN as a generator in the quantum GAN** to generate Earth observation images with a classical (hybrid model) or a quantum discriminator (quantum model). The inverse transform of the features will be essential in this case.