Bringing the power of Quantum Computing to Earth Observation

Alessandro Sebastianelli, Bertrand Le Saux

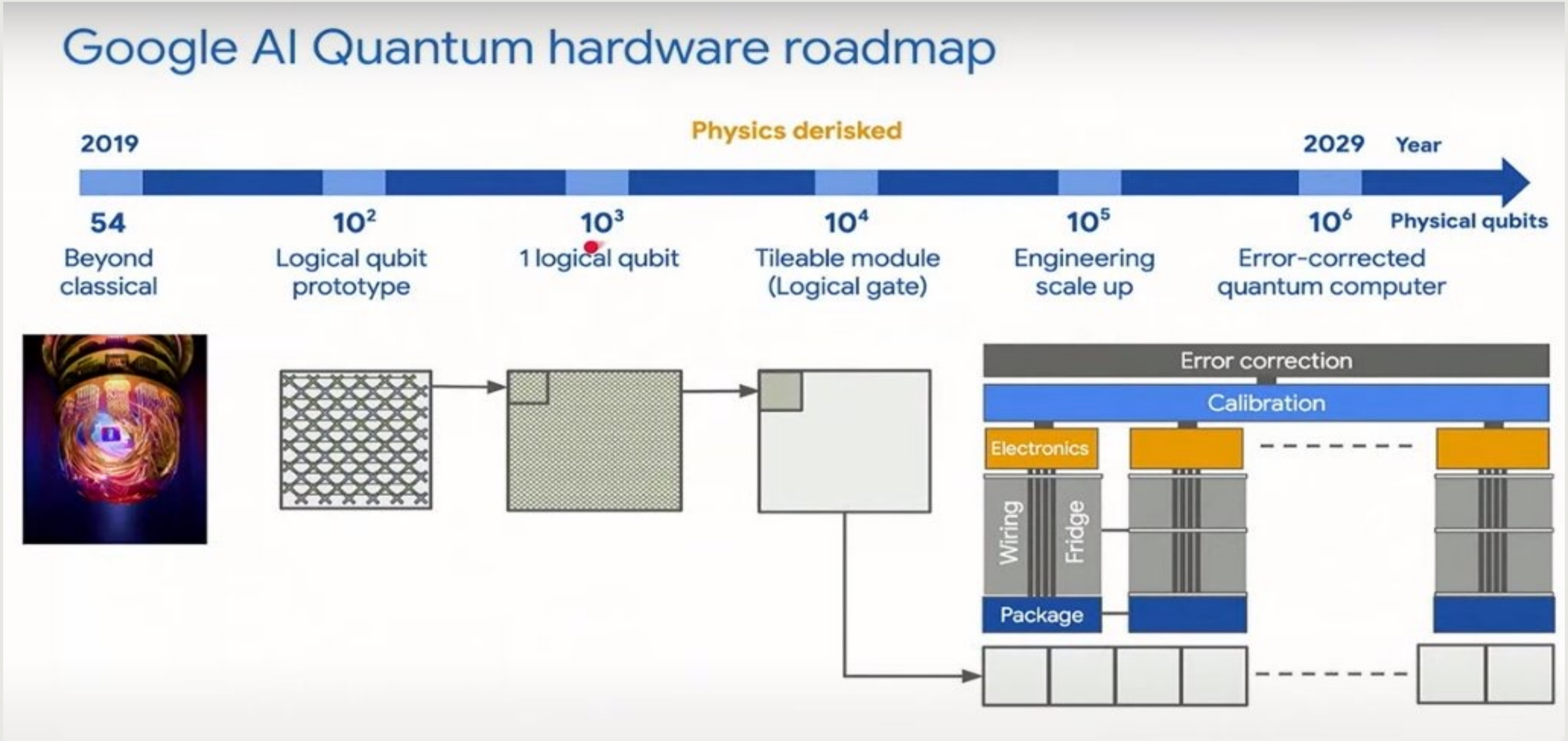
ESA EOP-S Φ-lab

30/01/2022

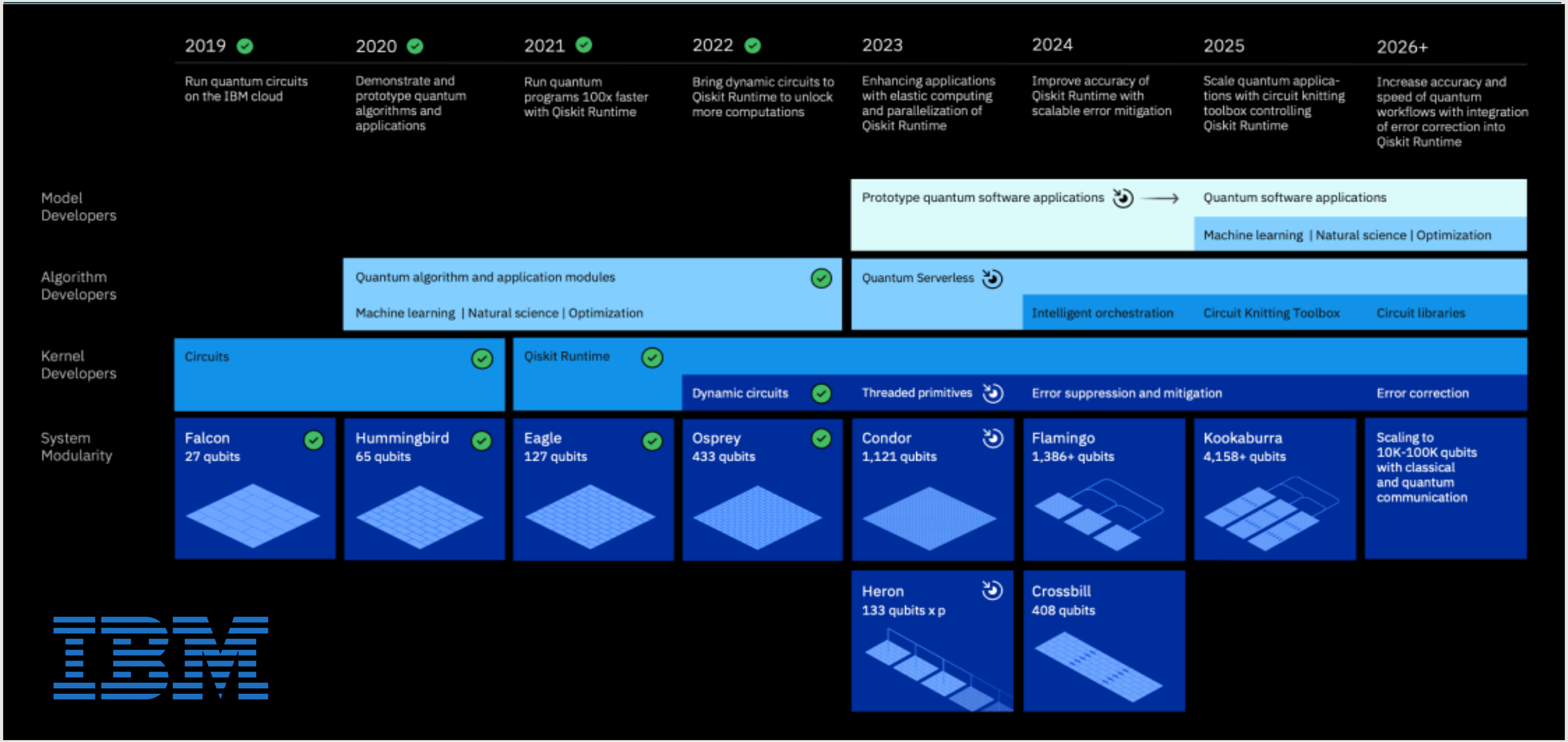
Quantum Computing Trends in 2023

Time magazine
February 2023 issue

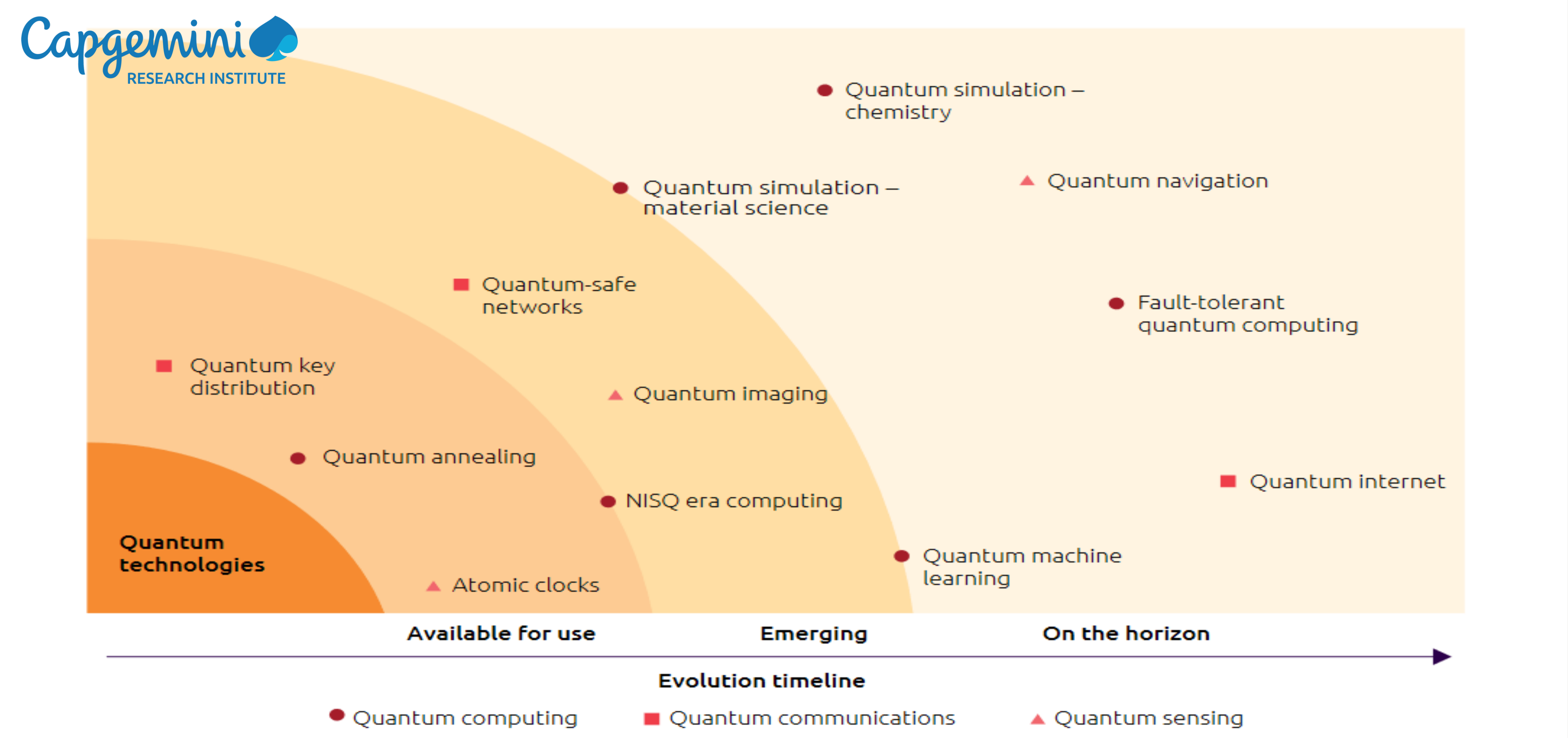
Quantum Computing Trends in 2023



Quantum Computing Trends in 2023



Quantum Computing Trends in 2023



Three directions

1. Roadmap definition (QC4EO studies)

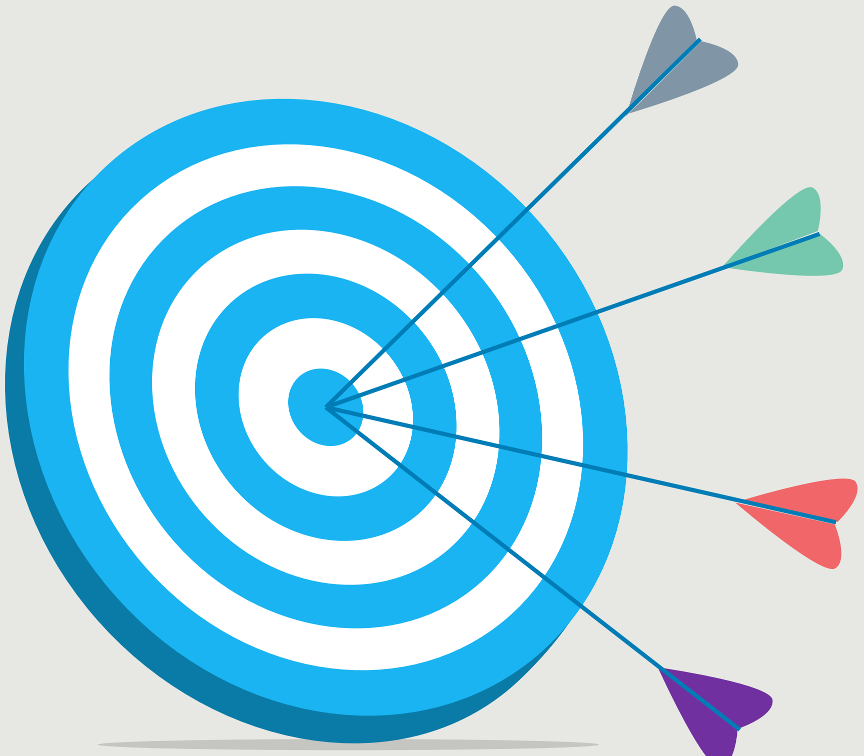
2. QML and QC Exploratory activities

3. QC4EO Network

Roadmap definition: QC4EO Studies

QC4EO Studies

2 projects during Q1 / Q2 2023 following ESA AO/1-11125/22/I-DT QUANTUM COMPUTING FOR EARTH OBSERVATION STUDY (QC4EO STUDY)



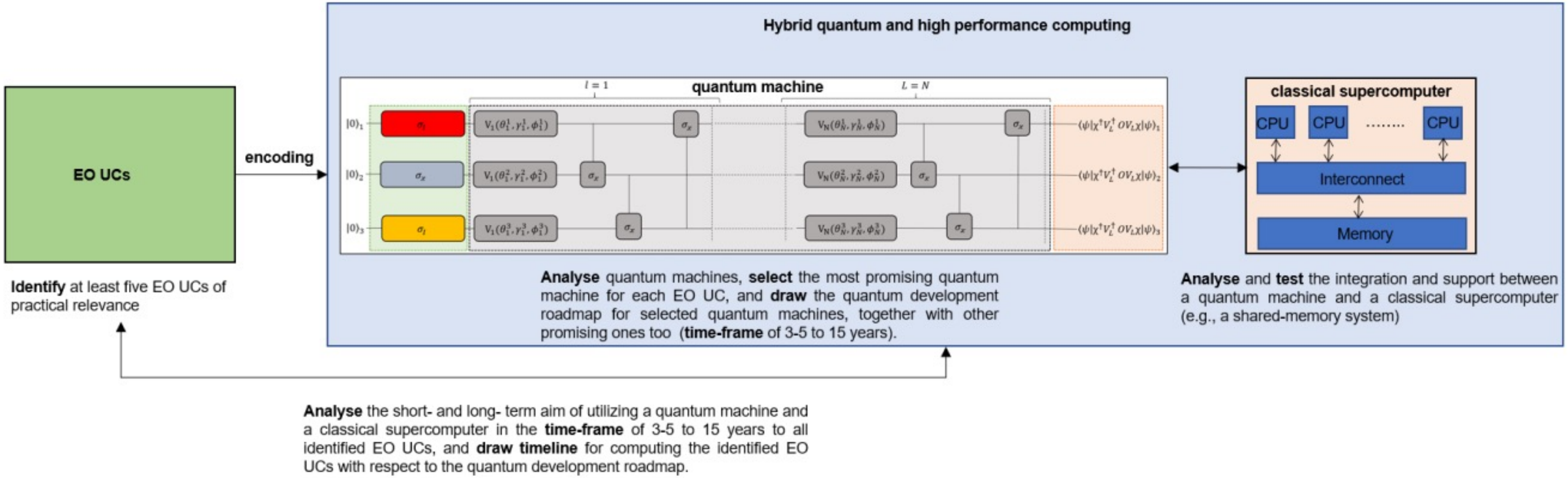
Objectives:

- ***Identify use cases relevant to the Earth Observation domain****, for which QC is expected to dramatically enhance computational performances with respect to traditional methods.*
- ***Provide options for QC or hybrid machine architectures*** *required to solve the identified QC4EO use cases, with the relevant sizing, e.g. in term of Qubits.*
- *Perform a* ***maturity and forecast assessment of the QC machine industry roadmaps****; and*
- ***Derive a credible QC4EO timeline of use cases*** *that could take advantage of a QC approach*

ESA Contract No. 4000140122/22/I-DT

Quantum Advantage for EO (QA4EO) project overview

- Identify hard Earth observation use cases (EO UCs) for quantum computers (e.g., quantum machines) or a hybrid approach
- Analyse quantum machines according to their number of qubits, errors, and so on
- Draw the roadmap of quantum computers



Quantum Advantage for Earth Observation

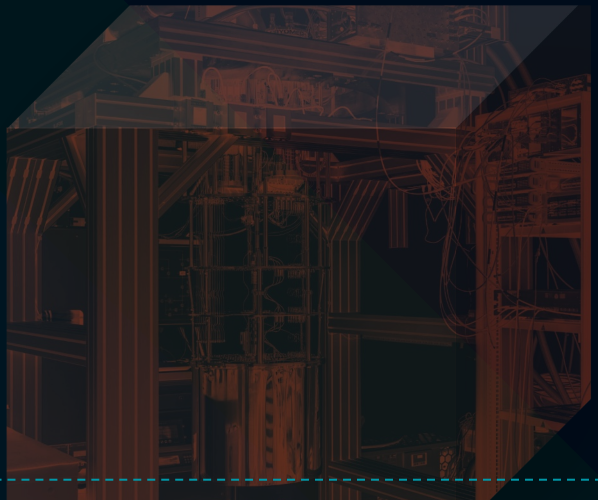
Project duration: **4 months (February to May 2023)**

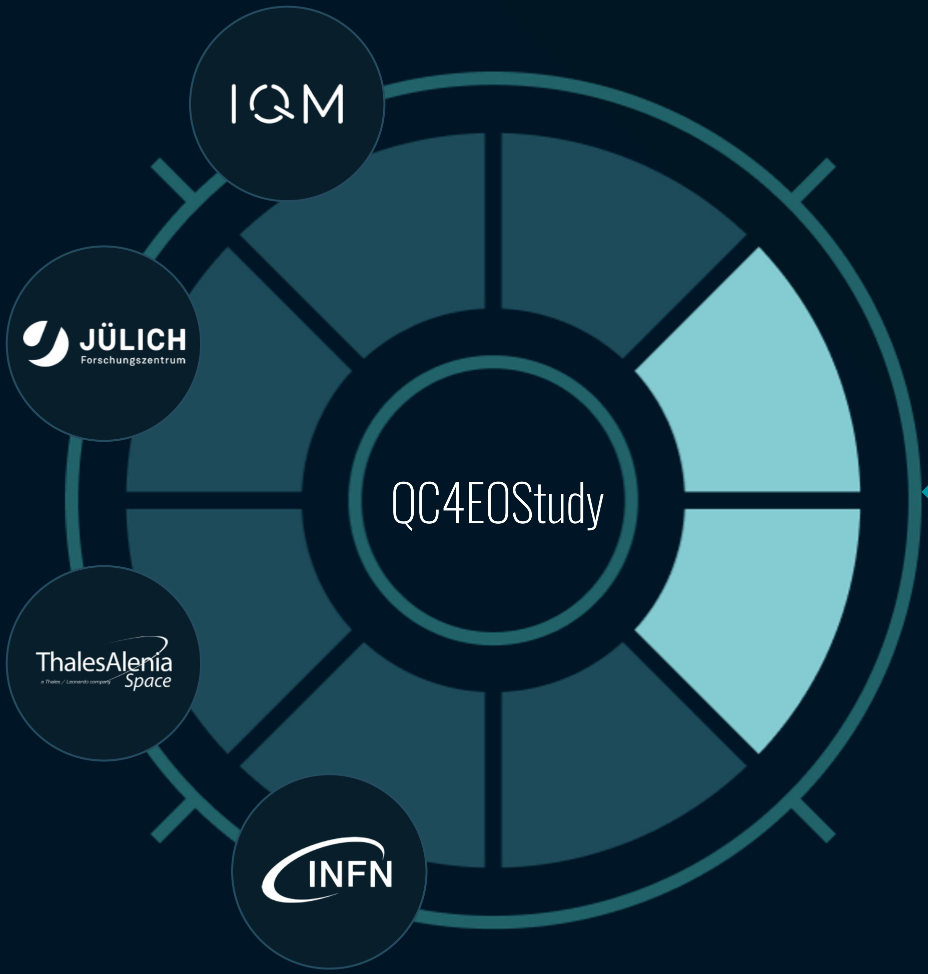
Prime-contractor: **DLR**
Sub-contractors: **VTT, CSC, SYDERAL, ETOS, Jagiellonian University**

Use-cases:

I. Variational quantum algorithms for EO Image processing
II. Climate adaptation digital twin hpc+qc workflow
III. Earth land cover understanding
IV. Feature selection for environmental monitoring hyperspectral imagery
V. Uncertainty quantification for remotely-sensed datasets

Quantum
COMPUTING FOR EARTH OBSERVATION





Can QC offer advantages to EO applications within a medium to long timeframe (between the next 3-5 to 15 years)? What hardware developments are necessary to achieve this quantum advantage?

OPTIMAL SOLUTIONS	BETTER MODELLING
SPEED-UP	ENERGY EFFICIENCY

Potential quantum advantages

esa

QC4EO Studies

Quantum Computing for Earth Observation

Project duration: 5 months (March to August 2023)
Prime-contractor: ForschungsZentrum Jülich (FZJ)
Sub-contractors: TASF, TASI, INFN, IQM

High-level list of identified use-cases:

Scenario n° 1 – Phase Unwrapping problem for interferometric SAR applications
Scenario n° 2 – Quantum Fourier Transform for SAR raw dara processing
Scenario n° 3 – Satellite Image Time Series Classification
Scenario n° 4 – Optical Agile Satellites Mission Planning
Scenario n° 5 – Multiple-view Geometry on optical images
Scenario n° 6 – Digital beamforming
Scenario n° 7 – Quantum algorithms for SAR raw data compression
Scenario n° 8 – Quantum algorithms for SAR image segmentation

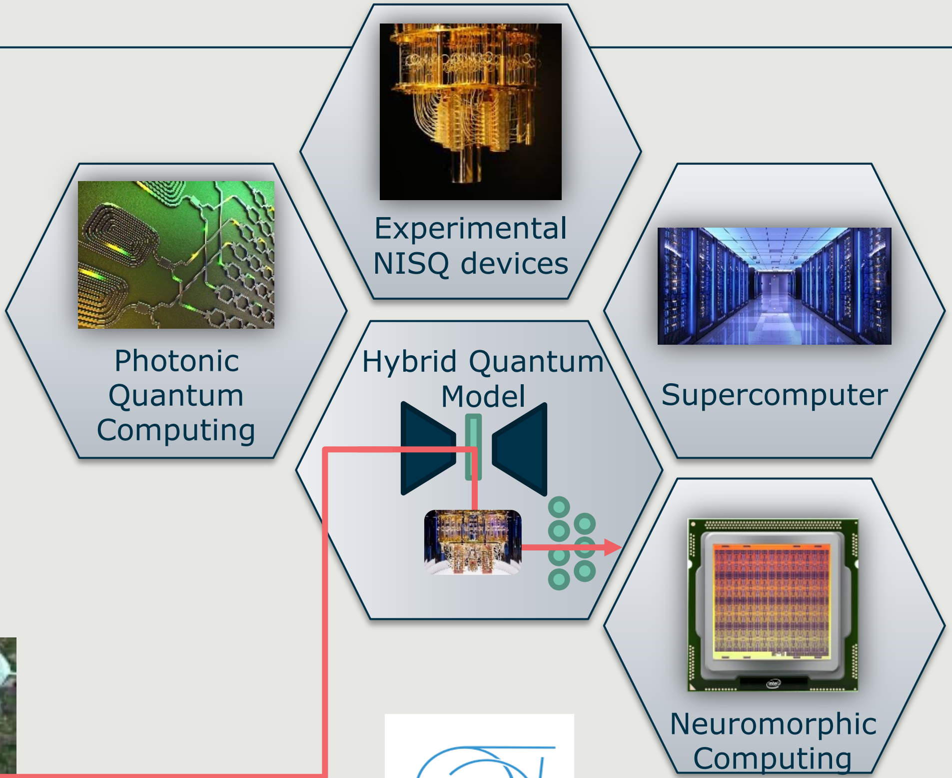
Exploratory activities

Exploratory activities in QML and Quantum Computing

Explore the potential of Quantum Machine Learning for Earth Observation use cases

Devise hybrid quantum classical AI models in high performance computing environments

Build a strong community of experts in both Quantum Computing and Earth Observation



CERN

NICOLAUS COPERNICUS ASTRONOMICAL CENTER OF THE POLISH ACADEMY OF SCIENCES

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO

JÜLICH Forschungszentrum

JAGIELLONIAN UNIVERSITY IN KRAKÓW

Exploratory activities in QML and Quantum Computing

➢ **Hybrid Classical Quantum Networks** (Quantum Convnets, Quantum GANs, Recurrent nets)

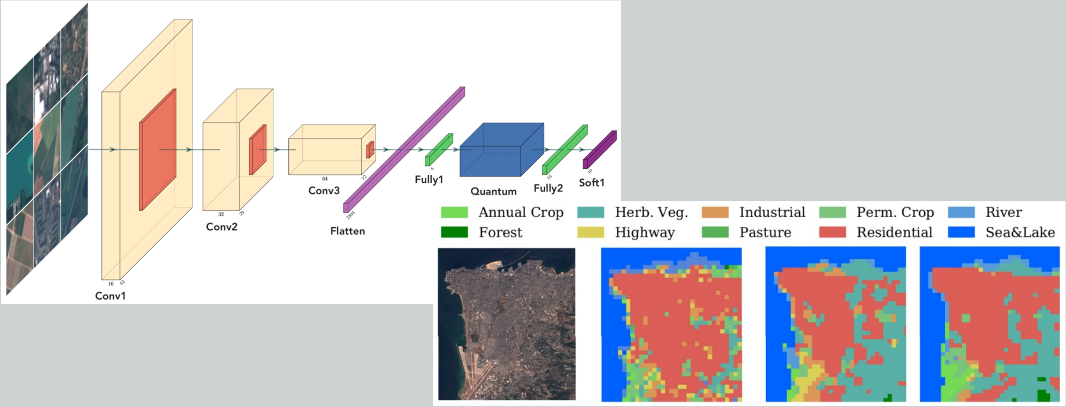
Case Study 1: Hybrid QCNN for EO classification

Use-case: EO image classification for land-use and land-cover.

Approach: Hybrid Quantum Classical CNNs enrich standard conv nets with a quantum layer!

Findings:

- Successful Proof of concept, with slightly better performances than comparable CNNs thanks to entanglement.



Sebastianelli et al. "On Circuit-based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification", IEEE JSTARS (15) 2021

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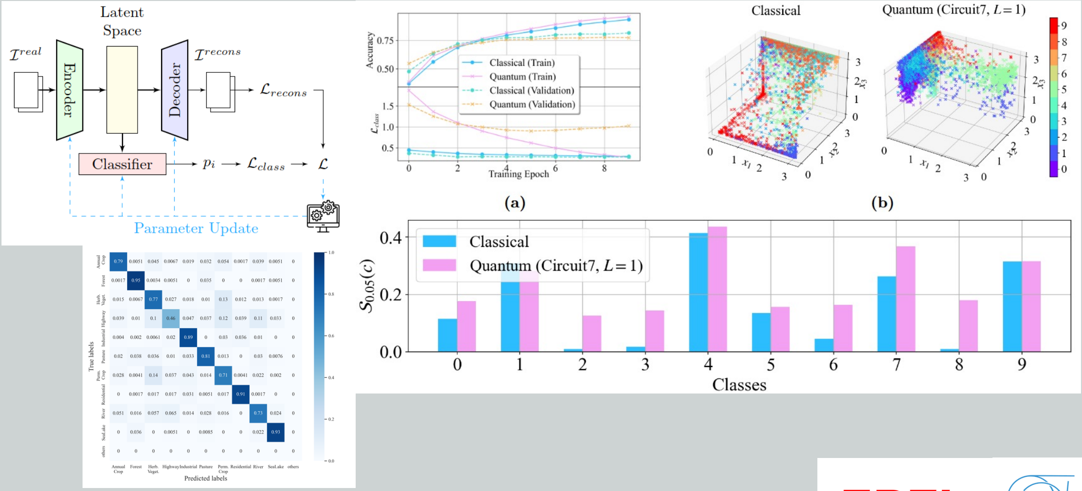
Case Study 2: Hybrid QCNN Expressivity

Use-case: EO image classification

Approach: Hybrid models with latent space embedding

Findings:

- Investigation of Quantum Ansätze: better expressivity with circuits with two-qubit SU 4 state
- End-to-end Proof of Concept for EO image classification with SOTA performances



Chang et al., "Quantum Conv Circuits for EO image classif.", IGARSS 2022

EPFL CERN

Exploratory activities in QML and Quantum Computing

➢ Exploring **Quantum Kernels** (e.g. Projected Quantum Features, SVMs…)

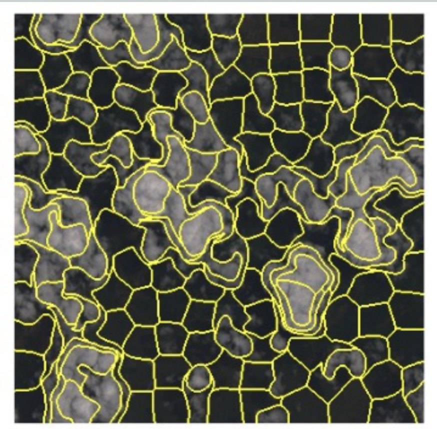
Case Study 3: Circuit-based Quantum SVM

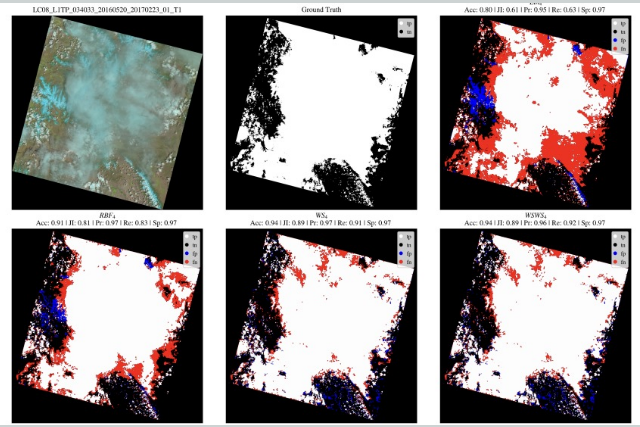
Use case: cloud detection in multispectral EO images.

Approach: Hybrid Support Vector Machines (SVMs) with **gate-based quantum kernels**.

Findings:

- End-to-end pipeline to embed and process EO data with small NISQ circuits.
- Successful Proof of Concept, with results on par with standard SVM thanks to Quantum Kernel Target Alignment.





Miroszewski, A., Mielczarek, J., Czelusta, G., Szczepanek, F., Grabowski, B., Le Saux, B., & Nalepa, J. (2023). Detecting Clouds in Multispectral Satellite Images Using Quantum-Kernel Support Vector Machines. arXiv preprint arXiv:2302.08270.

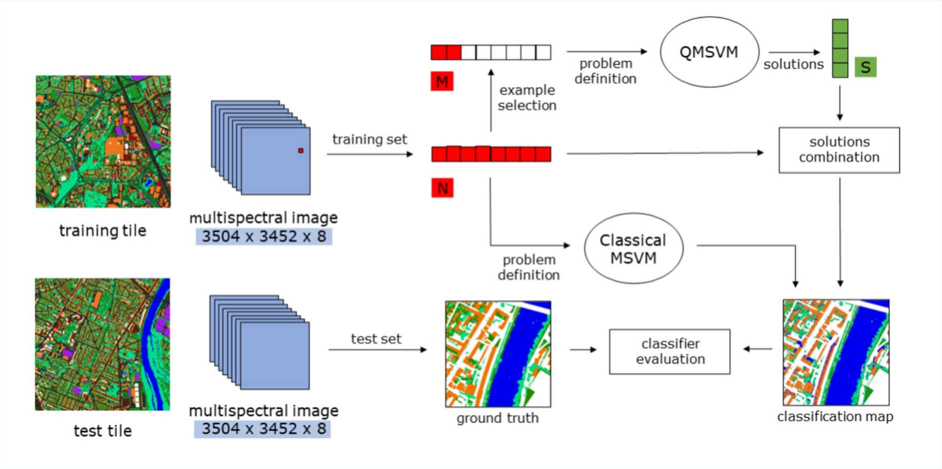
Case Study 4: Annealing-based Quantum SVM

Use case: Classification of multispectral EO data.

Approach: Hybrid Support Vector Machines (SVMs) with **Julich SC Quantum Annealer**.

Findings:

- Advantage Annealer operates only a limited number of samples for Q optimization…
- …. But execution times increase linearly!



Delilbasic, A., Le Saux, B., Riedel, M., Michielsen, K., & Cavallaro, G. (2023). A Single-Step Multiclass SVM based on Quantum Annealing for Remote Sensing Data Classification. arXiv preprint arXiv:2303.11705.

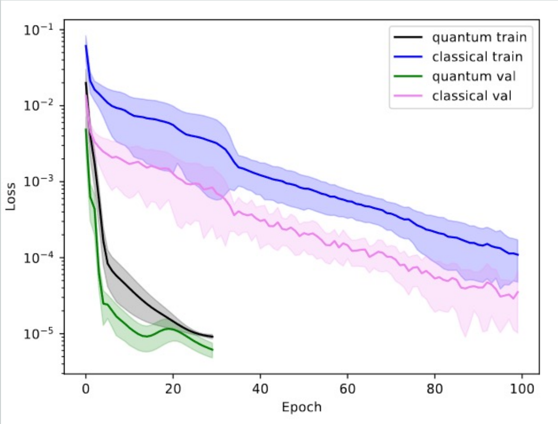
Exploratory activities in QML and Quantum Computing

➢ **Hybrid Classical Quantum Networks** (Quantum Convnets, Quantum GANs, Recurrent nets)

Case Study 5: Continuous-variable QC RNNs

Use case: Earth Systems observation and prediction.
Approach: Recurrent Neural Networks for time-series on Continuous-Variable QC.

Findings:
- Promises of faster training convergence
- For a small number of trainable parameters, it can achieve lower losses than its classical counterpart.



Siemaszko, McDermott, Buracsewski, Le Saux & Stobinska "Rapid training or recurrent quantum neural networks", **QTML 2022 / Qu Mach. Intell. 2023**

UNIVERSITY OF WARSAW

Case Study 6: Quantum Generative AI

Use case: Generative modelling and synthesis of images.
Approach: Quantum Generative Adversarial Networks (QGANS) : Quantum Generator + Classical Discriminator.

Findings:
- Trick #1: Latent space embedding by pretrained autoencoder
- Trick #2: Continuous, Style-based quantum GAN
- Successful image generation for varied image types
- Faster and better performances (in terms of distribution mapping) with less parameters

Chang et al., to appear

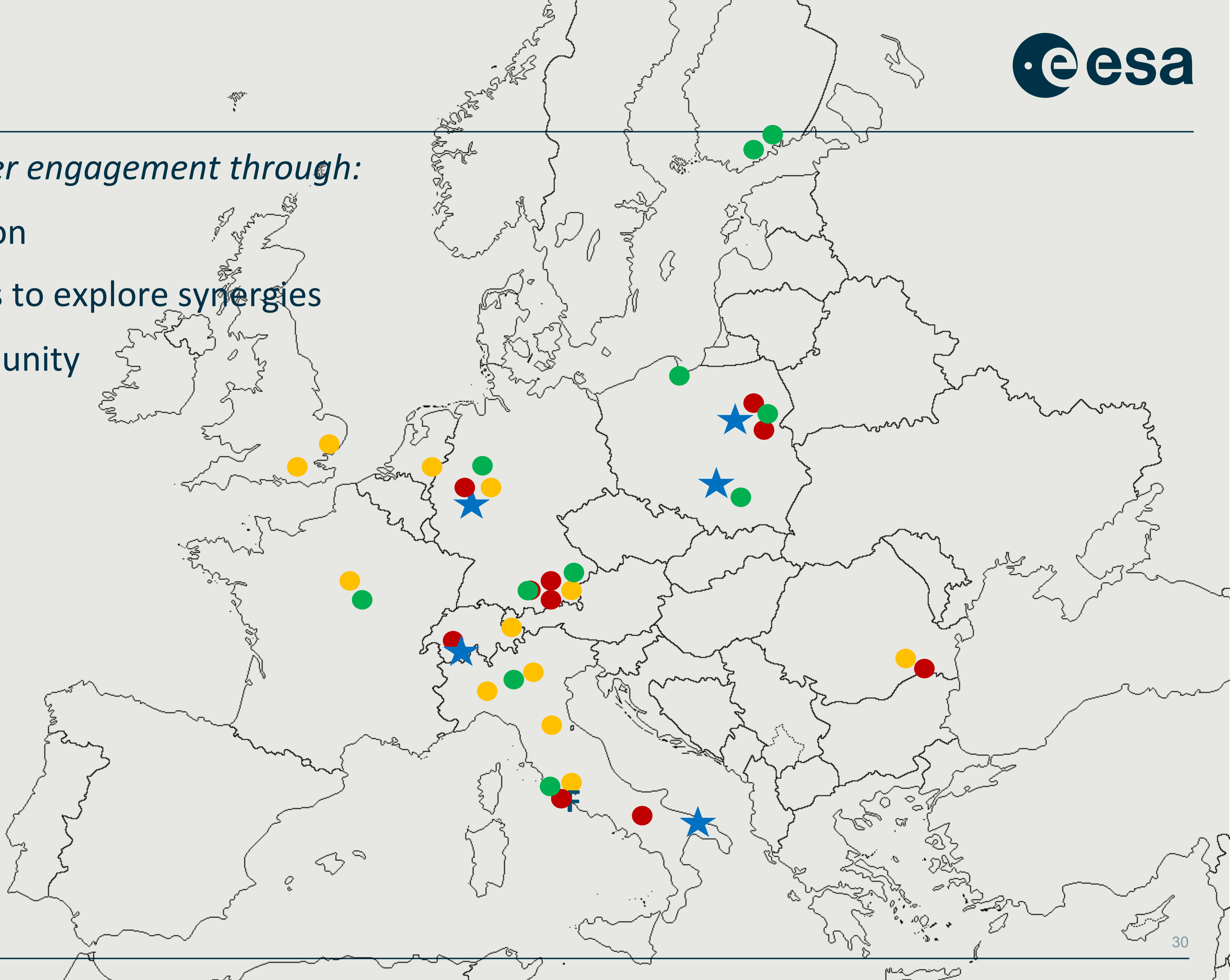
CERN EPFL

QC4EO Network

QC4EO Network

Community building and stakeholder engagement through:

- Workshop and event organisation
- Consult QC and EO communities to explore synergies
- Support emerging QCxEO community



- ● QC4EO Study
- ★ Co-funded research
- ● Partners / visitors
- ● Community / events

QC4EO Network: workshops and events

- 2019 Workshop on Quantum Processing: from Quantum Computing to Earth Observation in Rome,
  https://philab.phi.esa.int/workshop-quantum-for-earth-observation/
- 2021 ESA-Ellis Workshop on Quantum Algorithms and Machine Learning for EO applications,
  https://ellisqphml.github.io/ellisphilab2021
- 2021 Φ-week QC4EO session in Frascati,
  https://phiweek.esa.int
- 2021 ESA 5th Quantum Conference Quantum Computing session,
  https://atpi.eventsair.com/5th-quantum-technology-conference/
- 2022 Living Planet Symposium, Agora Session on “Future of Computing for FutureEO”
- 2022 QTML 2022 Industry Panel
- 2023 ESA 6th Quantum Conference Quantum Computing session,
  https://nikal.eventsair.com/6th-quantum-technology-conference

QC4EO Network: organisations

Stakeholder engagement

- AI-enhanced Quantum Computing for EO: Joint initiative between CERN and ESA-EOP
- QC4EO JP: Consultation with CERN, DLR, TU Munich, LRZ, Ellis, etc…
- Companies: IBM, Quantinuum, Quandela, Thales, Xanadu, etc.

Community events and thematic initiatives

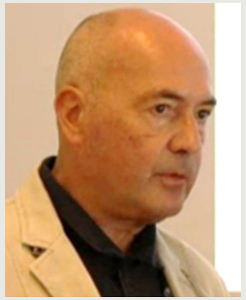
- IEEE GRSS High-performance and Disruptive Computing (HDCRS) Summer School, May 2022, 2023
  https://www.hdc-rs.com
- CINECA **Introduction to Quantum Computing School** June 2023
- Quantum Open Software Foundation mentoring https://qosf.org/
- Quantum Climate initiative https://q4climate.github.io/

Publications

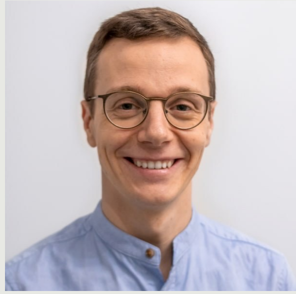
- IEEE JSTARS Special Issue on "Quantum resources for Earth Observation" → 2021 / 2022
  Ed. M. Datcu (DLR), J. Le Moigne (NASA), B. Le Saux (ESA) → https://ieeexplore.ieee.org

QC4EO Network: visiting researchers

Senior visiting researchers:



Mihai Datcu
(Politehnica Uni of Bucharest)



Gabriele Cavallaro
(Forschungszentrum Jülich)

Piotr Gawron
(CAMK / Polish Acad of Sciences)

Early-career researchers:

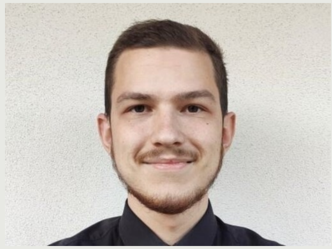
Michal Siemaszko
(PhD, Univ. Warsaw)

Alice Barthe
(PhD, CERN / Leiden Uni)

Andrea Ceschini
(PhD, La Sapienza)

Francesca de Falco
(MSc., La Sapienza)

Francesco Mauro
(PhD, Uni. Sannio)



Amer Delilbasic
(PhD, Uni of Iceland / FZ Jülich)

- **We are welcoming visiting researchers from academia and industry!**
- **Spend short stays or residencies at the Φ-lab to mingle with EO, AI, and QC experts!**
- **Let’s get in touch!**

Conclusions

ESA Φ-lab's Initiative on Quantum Computing for Earth Observation (QC4EO)

General perspectives:

- *Increase the **mutual awareness** of the needs and capabilities of the **Quantum Computing** and **Earth Observation** communities*

- *Create new **synergies**, building on shared experience in **AI**, optimisation, and **high-performance computing***

- *Prepare the ground for the opportunities that will be presented when the quantum community will be able to produce hardware and software for applied problems*

ESA Φ-lab's Initiative on Quantum Computing for Earth Observation (QC4EO)

Practical perspectives:

- *Look for **practical applications and use-cases**, enabled by increased quantum volume*
- *Understand the **advantages** (faster, better, etc.?) brought by QC with **exploratory activities***
- ***Design hybrid computing** frameworks including traditional CPU, GPU, HPC and new paradigms such as quantum and neuromorphic computing for optimal problem solving*

Bringing the power of Quantum Computing to Earth Observation

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- *Join ESA Φ-lab@ESRIN: https://jobs.esa.int/*
- *Contact: alessandro.sebastianelli@esa.int, bertrand.le.saux@esa.int*

SAVE THE DATE!
6th ESA Quantum Technology Conference | 19 – 21 September 2023 | Matera, Italy

On Circuit-Based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification

Alessandro Sebastianelli, Bertrand Le Saux

09/06/2023

About Me

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European Space Research Institute (ESRIN/ESA)

ESA Φ-lab https://philab.esa.int/

Introduction

IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 15, 2022 565

On Circuit-Based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification

Alessandro Sebastianelli, *Student Member, IEEE*, Daniela Alessandra Zaidenberg, *Student Member, IEEE*, Dario Spiller, *Member, IEEE*, Bertrand Le Saux, *Member, IEEE*, and Silvia Liberata Ullo, *Senior Member, IEEE*

***Abstract*—This article aims to investigate how circuit-based hybrid quantum convolutional neural networks (QCNNs) can be successfully employed as image classifiers in the context of remote sensing. The hybrid QCNNs enrich the classical architecture of convolutional neural networks by introducing a quantum layer within a standard neural network. The novel QCNN proposed in this work is applied to the land-use and land-cover classification, chosen as an Earth observation (EO) use case, and tested on the EuroSAT dataset used as the reference benchmark. The results of the multiclass classification prove the effectiveness of the presented approach by demonstrating that the QCNN performances are higher than the classical counterparts. Moreover, investigation of various quantum circuits shows that the ones exploiting quantum entanglement achieve the best classification scores. This study underlines the potentialities of applying quantum computing to an EO case study and provides the theoretical and experimental background for future investigations.**

***Index Terms*—Earth observation (EO), image classification, land-use and land-cover (LULC) classification, machine learning (ML), quantum computing (QC), quantum machine learning (QML), remote sensing.**

methodologies have also progressed to accommodate larger and higher resolution datasets. Image classification techniques are constantly being improved to keep up with the ever expanding stream of Big Data, and as a consequence, artificial intelligence (AI) techniques are becoming increasingly necessary tools [5], [6].

Given the need to help expand the processing techniques to deal with these high-resolution Big Data, EO is now looking toward new and innovative computation technologies [7]. This is where quantum computing (QC) will play a fundamental role [8]. Today, there is a number of differing quantum devices, such as programmable superconducting processors [9], quantum annealers [10], and photonic quantum computers [11]. However, QC still presents some technological limitations, as reported in [12] with a special concern with noise and limited error correction. Specific algorithms, namely, the noisy intermediate-scale quantum (NISQ) computing algorithms, have been designed to tackle these issues [13].

Partners

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Massachusetts Institute of Technology

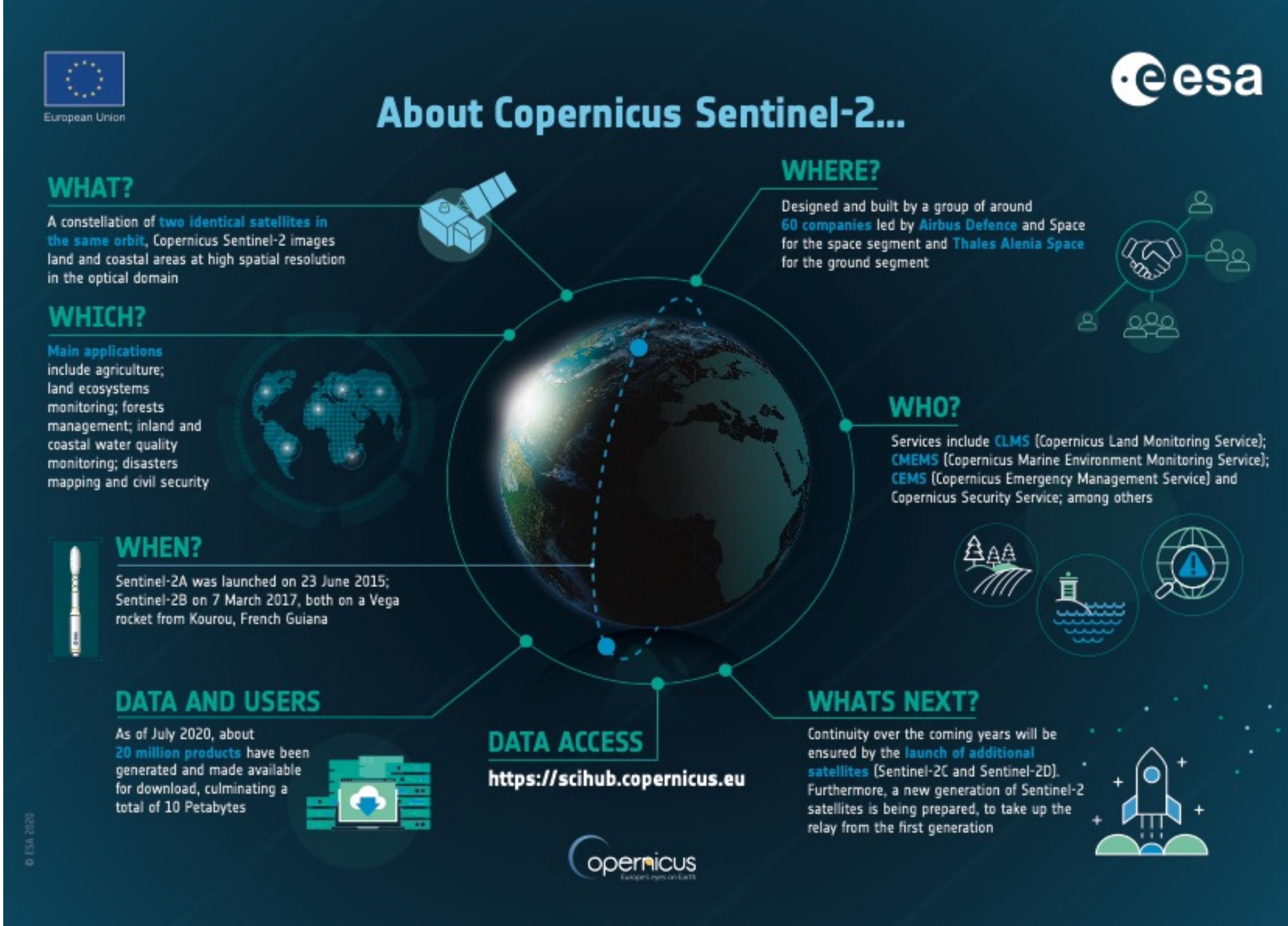
SAPIENZA UNIVERSITÀ DI ROMA

One of the first peer-reviewed paper about Quantum Computing, Quantum Machine Learning and Earth Observation

DATASET

Dataset [1]

- Satellite Platform



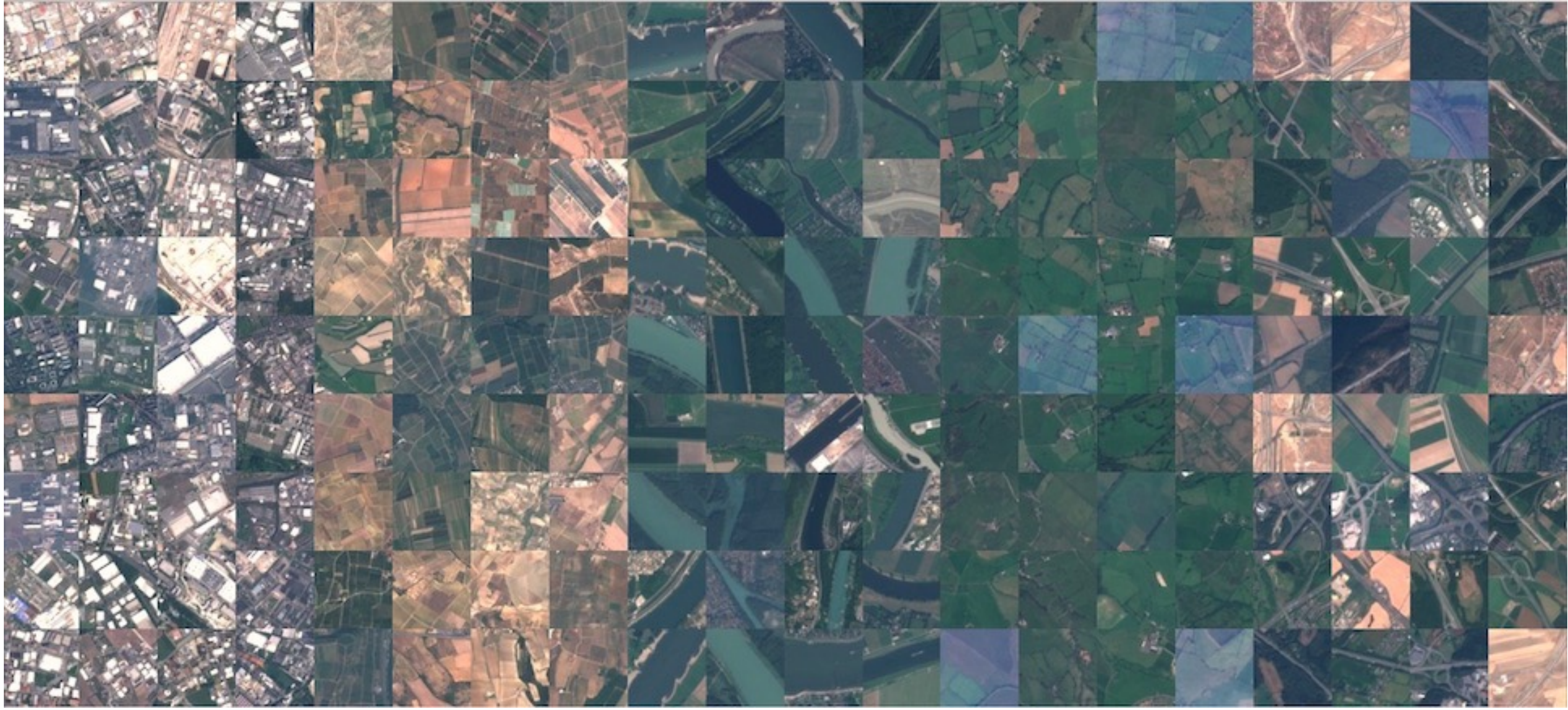
Courtesy of https://sentinel.esa.int/web/sentinel/missions/sentinel-2

Dataset [2]

- Satellite Platform
- S2 data

Dataset [3]

- Satellite Platform
- S2 data
- Chosen Dataset



EuroSAT: Land Use and Land Cover Classification with Sentinel-2

Dataset based on Sentinel-2 satellite images covering 13 spectral bands and consisting out of 10 classes with in total 27,000 labelled and geo-referenced images.

https://github.com/phelber/EuroSAT

Dataset [4]

- Satellite Platform
- S2 data
- **Chosen Dataset**

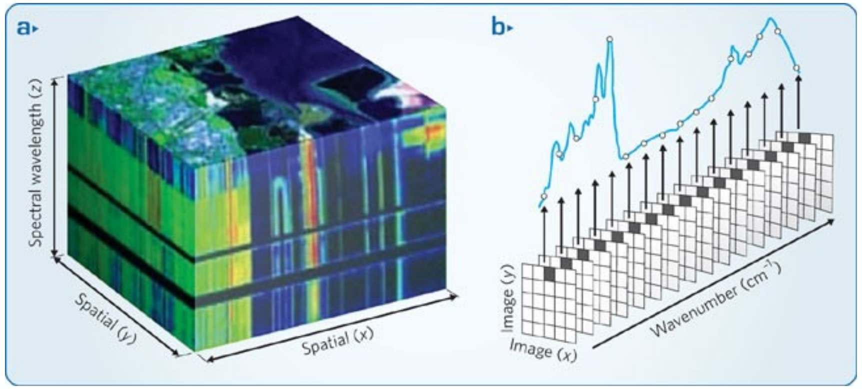
(**a**) Pasture (**b**) Highway (**c**) Permanent crop (**d**) Industrial (**e**) Annual crop

(**f**) Forest (**g**) Residential (**h**) River (**i**) SeaLake (**j**) Herbaceous Vegetation

Courtesy of https://www.mdpi.com/2072-4292/14/16/3995

Dataset in terms of ML

$X \in R^{N \times W \times H \times B}$ where $N = 27000,\ W = H = 64,\ B = 13$
$y \in R^{N \times C}$ where $N = 27000,\ C = 10$



Courtesy of https://www.nature.com/articles/nphoton.2009.205

Dataset [5]

- Satellite Platform
- S2 data
- Chosen Dataset
- **Train-Val split**

Training Set

Validation Set

Train-Val split 80%-20%

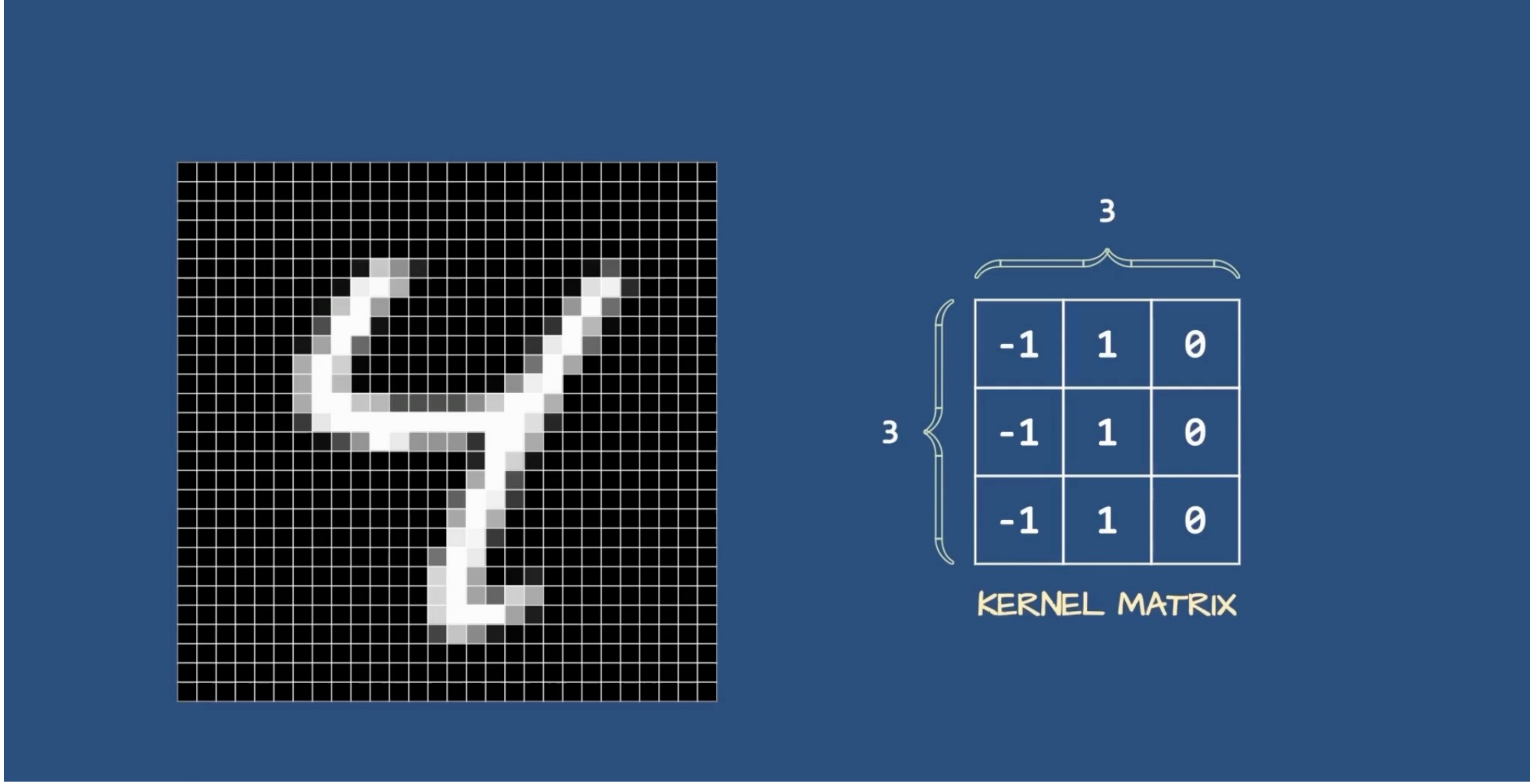
$X_{train} \in R^{M \times W \times H \times B}$ where $M = 21600,\ W = H = 64,\ B = 13$
$y_{train} \in R^{M \times C}$ where $M = 21600,\ C = 10$

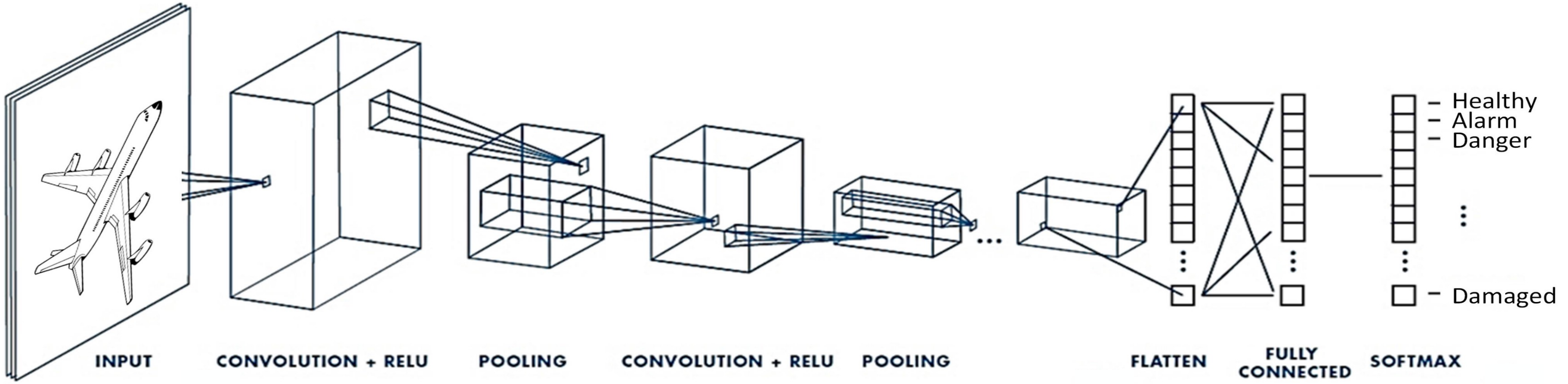
$X_{valid} \in R^{P \times W \times H \times B}$ where $P = 5400,\ W = H = 64,\ B = 13$
$y_{valid} \in R^{P \times C}$ where $\mathrm{P} = 5400,\ C = 10$

METHODOLOGY

Method [1]

- Convolutional Neural Networks

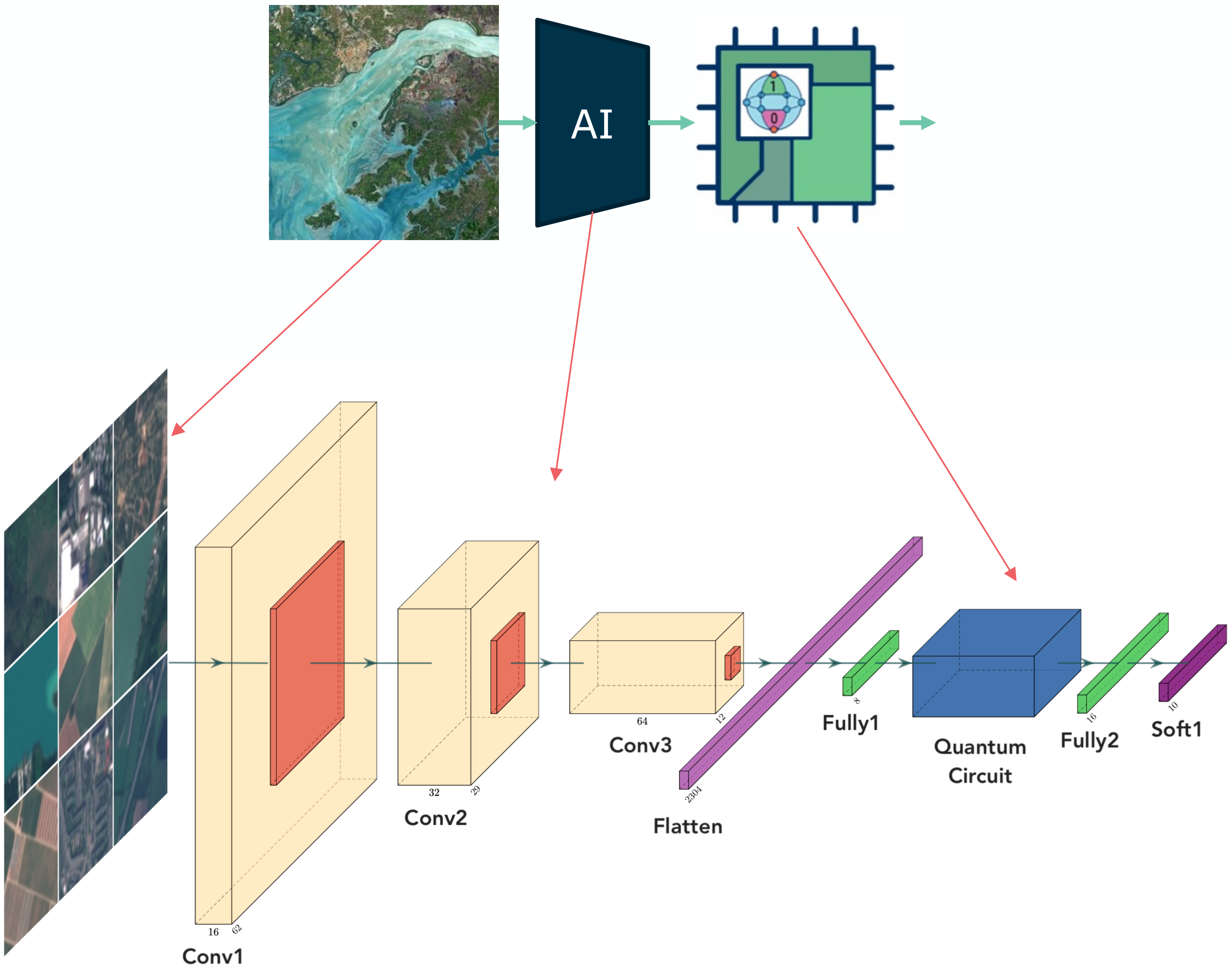




Method [2]

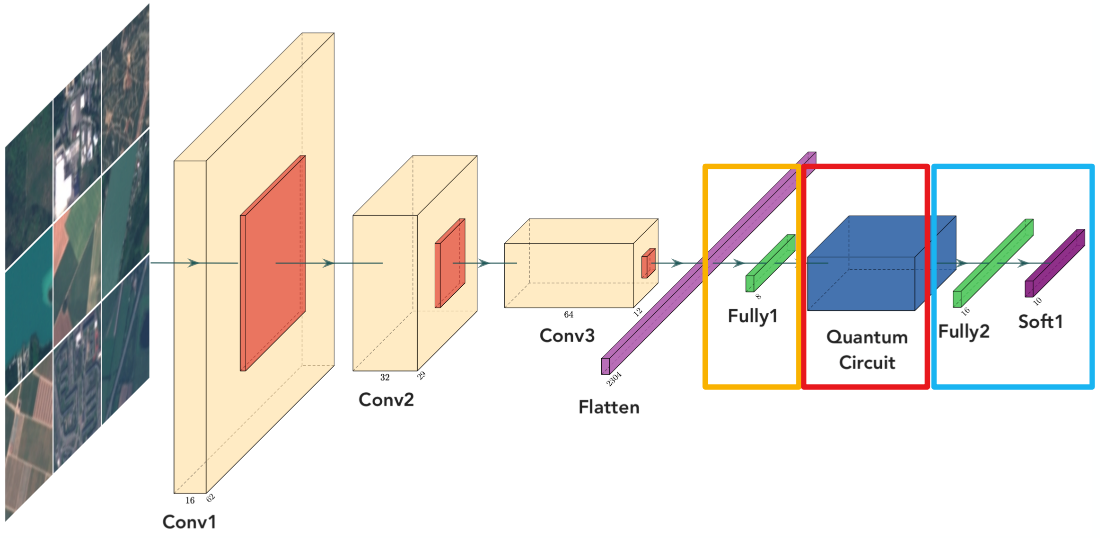
- Convolutional Neural Networks
- Hybrid Model

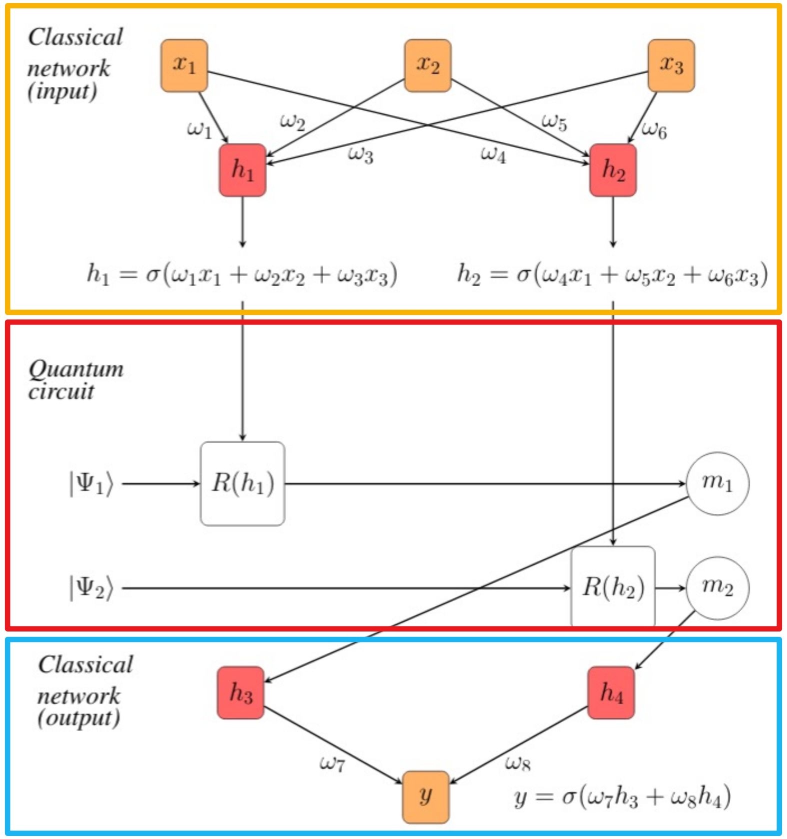
Late Hybrid Schemes



Method [3]

- Convolutional Neural Networks
- Hybrid Model
- **Data Embedding**





Variational Parametrized Quantum Circuit

A parameterized quantum circuit is a quantum circuit, where the rotation angles for each gate are specified by the components of a classical input vector.

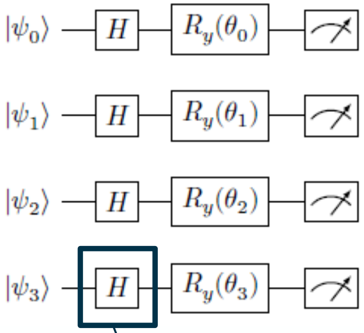
The outputs from the neural network's previous layer will be collected and used as the inputs for the parameterized circuit.

The measurement statistics of the quantum circuit can then be collected and used as inputs for the following hidden layer.

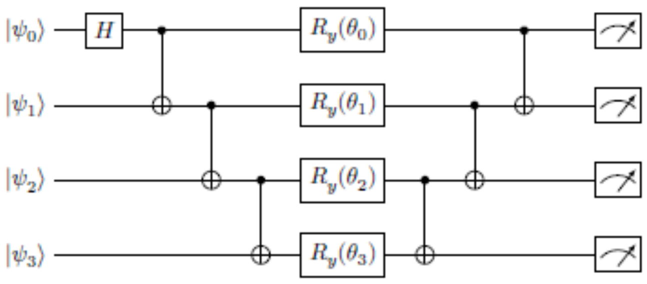
Method [5]

- Convolutional Neural Networks
- Hybrid Model
- Data Embedding
- **Circuit Definition**

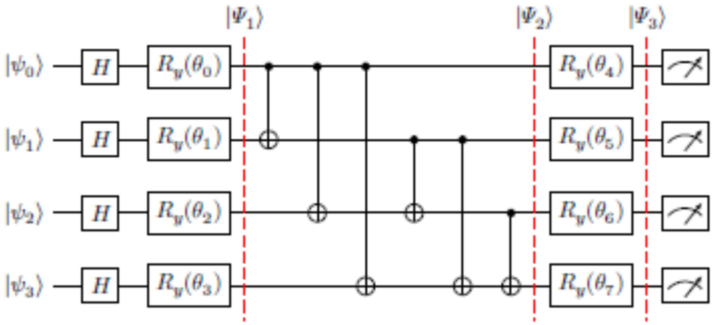
Circ 1



Circ 2

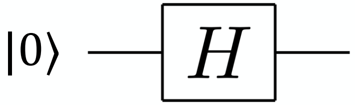


Circ 3



Hadamard Gate

Single qubit gate described by the matrix $\mathrm{H} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$



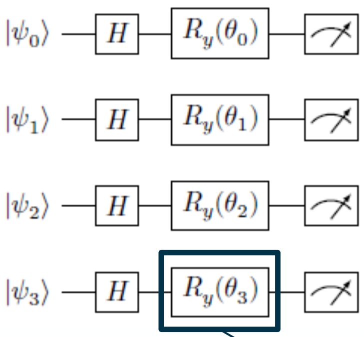
Starting from the single state qubit $|0\rangle$, the Hadamard gate returns the superposition of two states, namely the so-called *plus* state $|+\rangle$, i.e.

$$H|0\rangle = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}\begin{pmatrix} 1 \\ 0 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}}\begin{pmatrix} 1 \\ 0 \end{pmatrix} + \frac{1}{\sqrt{2}}\begin{pmatrix} 0 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle = |+\rangle$$

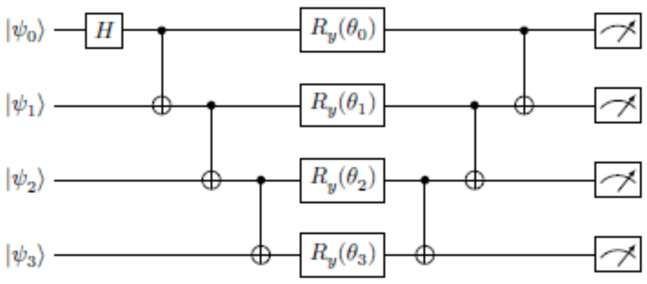
Method [6]

- Convolutional Neural Networks
- Hybrid Model
- Data Embedding
- **Circuit Definition**

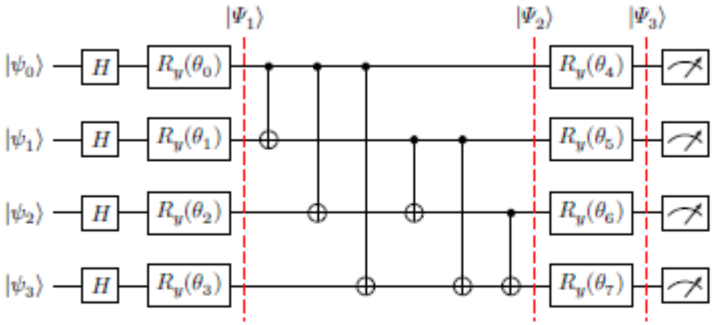
Circ 1



Circ 2



Circ 3



Rotation Gate $R_y(\theta)$ $R_x(\theta)$ $R_z(\theta)$

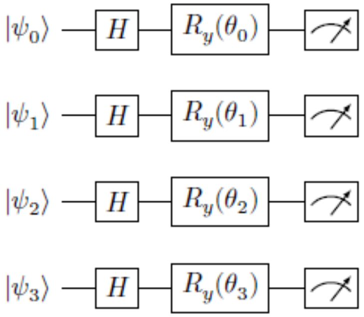
Single qubit gate described by the rotation matrices about the $\hat{x}$, $\hat{y}$, $\hat{z}$ axes of the Block sphere. The $R_y(\theta)$ used in our case is defined by:

$$R_y(\theta) = \begin{pmatrix} \cos\frac{\theta}{2} & -\sin\frac{\theta}{2} \\ \sin\frac{\theta}{2} & \cos\frac{\theta}{2} \end{pmatrix}$$

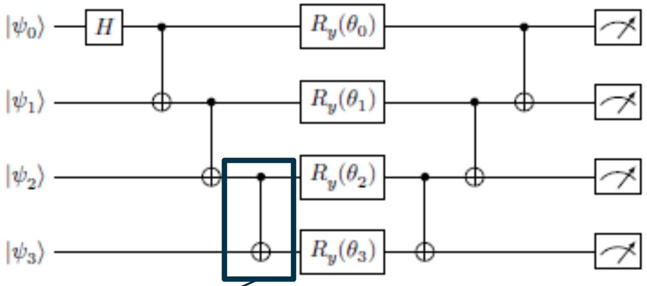
Method [7]

- Convolutional Neural Networks
- Hybrid Model
- Data Embedding
- **Circuit Definition**

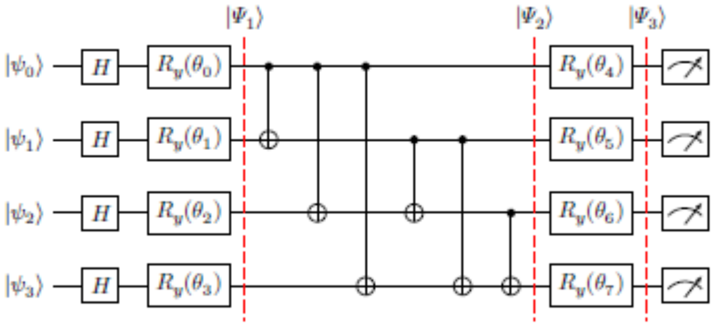
Circ 1



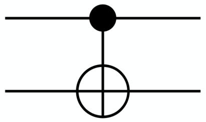
Circ 2



Circ 3



CNOT Gate



Two qubits gate described by the matrix:

$$U = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

When the input are basis states $|0\rangle$ and $|1\rangle$, the CNOT gate transforms the state

$$\alpha_{00}|00\rangle + \alpha_{01}|01\rangle + \alpha_{10}|10\rangle + \alpha_{11}|11\rangle$$

into

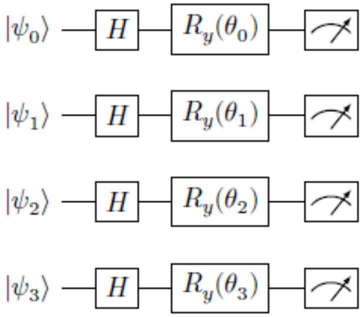
$$\alpha_{00}|00\rangle + \alpha_{01}|01\rangle + \alpha_{10}|11\rangle + \alpha_{11}|10\rangle$$

i.e., it flips the second qubit (the target qubit) if and only of the first qubit (the control qubit) is $|1\rangle$.

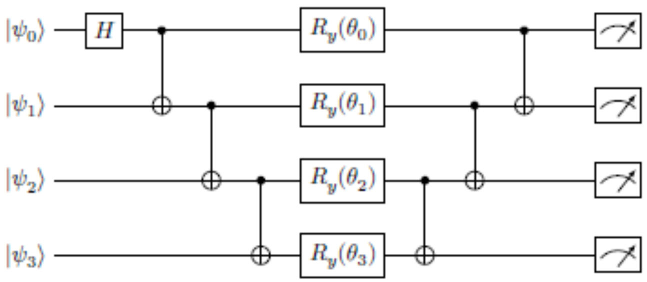
Method [8]

- Convolutional Neural Networks
- Hybrid Model
- Data Embedding
- **Circuit Definition**

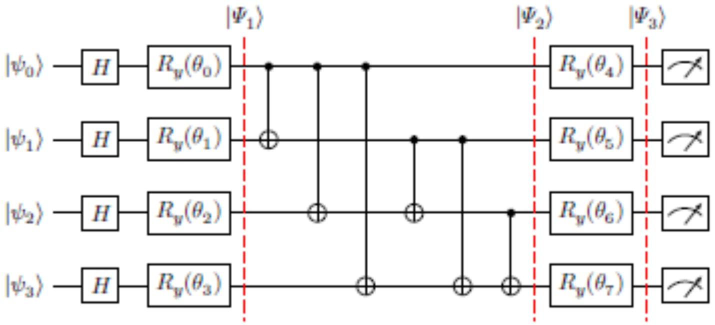
Circ 1



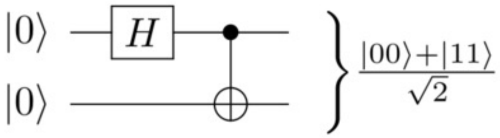
Circ 2



Circ 3



Bell State



The combination of Hadamard and CNOT gates is used to create an entangled Bell state

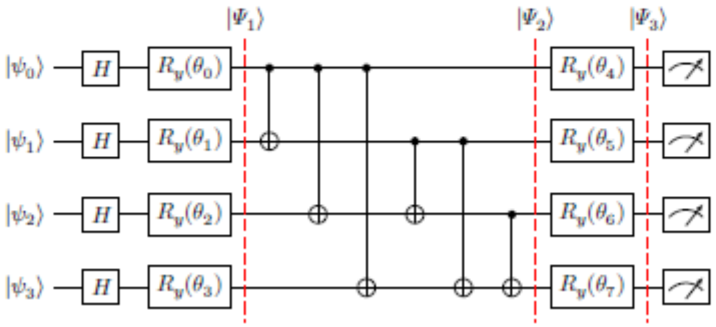
$$|\psi\rangle = \frac{1}{\sqrt{2}}|00\rangle + \frac{1}{\sqrt{2}}|11\rangle$$

The corresponding circuit shown in Fig. above is the basic building block of the quantum circuits investigated in our work, as it introduces entanglement in the circuit by enhancing the computation performances.

Method [9]

- Convolutional Neural Networks
- Hybrid Model
- Data Embedding
- Circuit Definition
- **Real Amplitude Circuit**

Circ 3



Considering identity rotations, i.e. $R_y(\theta) = I, i = 0 \dots 3$, the state before the CNOT gates considering the four inputs as $|0\rangle$, is represented by

$$|\psi_1\rangle = \left(\bigotimes_{i=0}^{3} H\right)|0000\rangle = \bigotimes_{i=0}^{3}(H|0\rangle) = \left(\frac{1}{\sqrt{2}}\right)^4 \bigotimes_{i=0}^{3}(|0\rangle + |1\rangle) =$$

$$= 0.25(|0000\rangle + |0010\rangle + |0011\rangle + |0001\rangle + |0100\rangle + |0110\rangle + |0111\rangle + |0101\rangle + |1000\rangle + |1010\rangle + |1011\rangle + |1001\rangle + |1100\rangle + |1110\rangle + |1101\rangle + |1111\rangle)$$

After the CNOT gates, it is easy to verify that this example state is unchanged, i.e. $|\psi_1\rangle = |\psi_2\rangle$ (but in general case it varies). Finally, the quantum parameters $\theta_i, i = 4, \dots 7$, are implemented by means of the final four rotations, the final state is given by

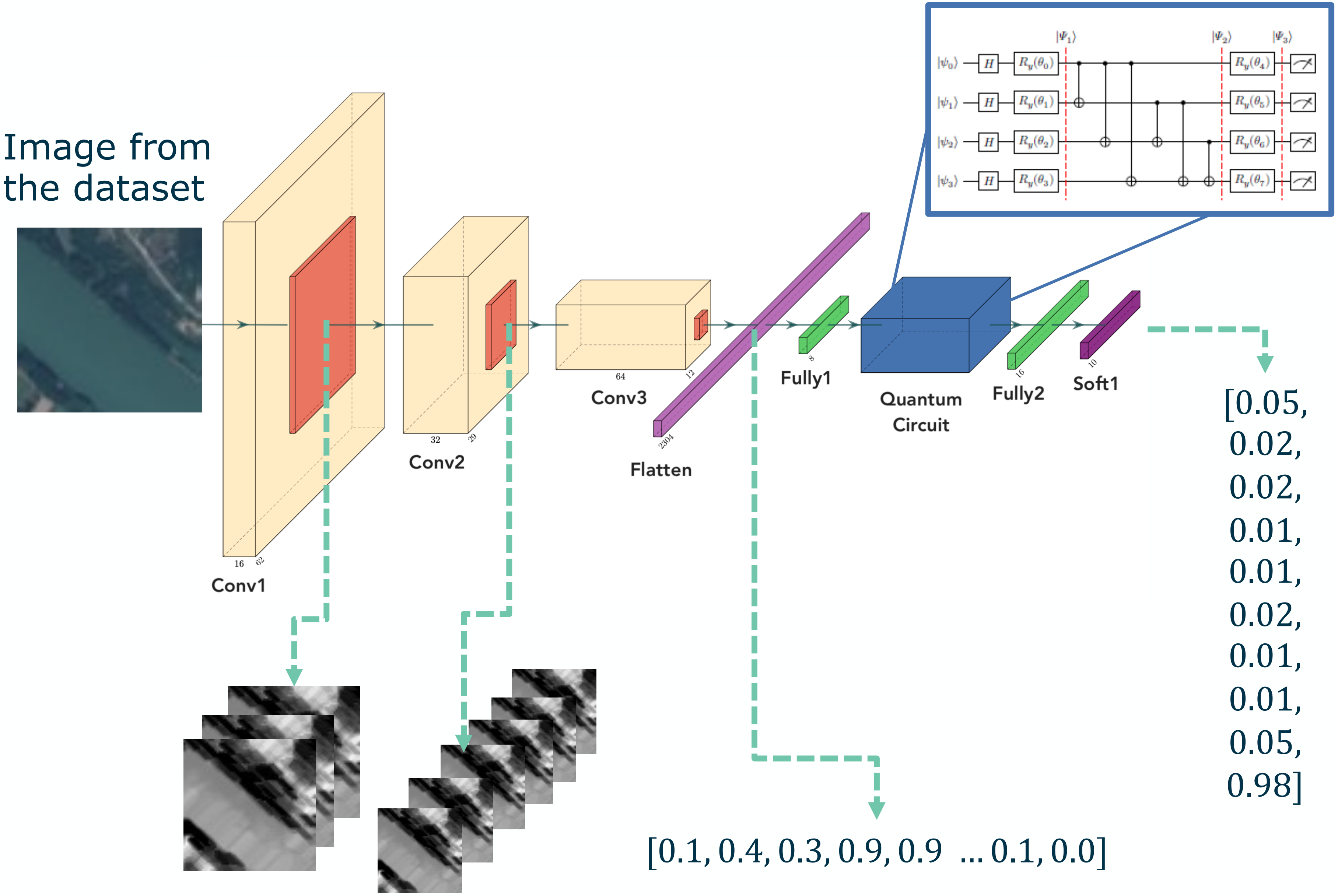
$$|\psi_3\rangle = \bigotimes_{i=0}^{3} R_y(\theta_i)|\psi_2\rangle$$

https://quantum-computing.ibm.com/composer/

TRAINING

Training [1]

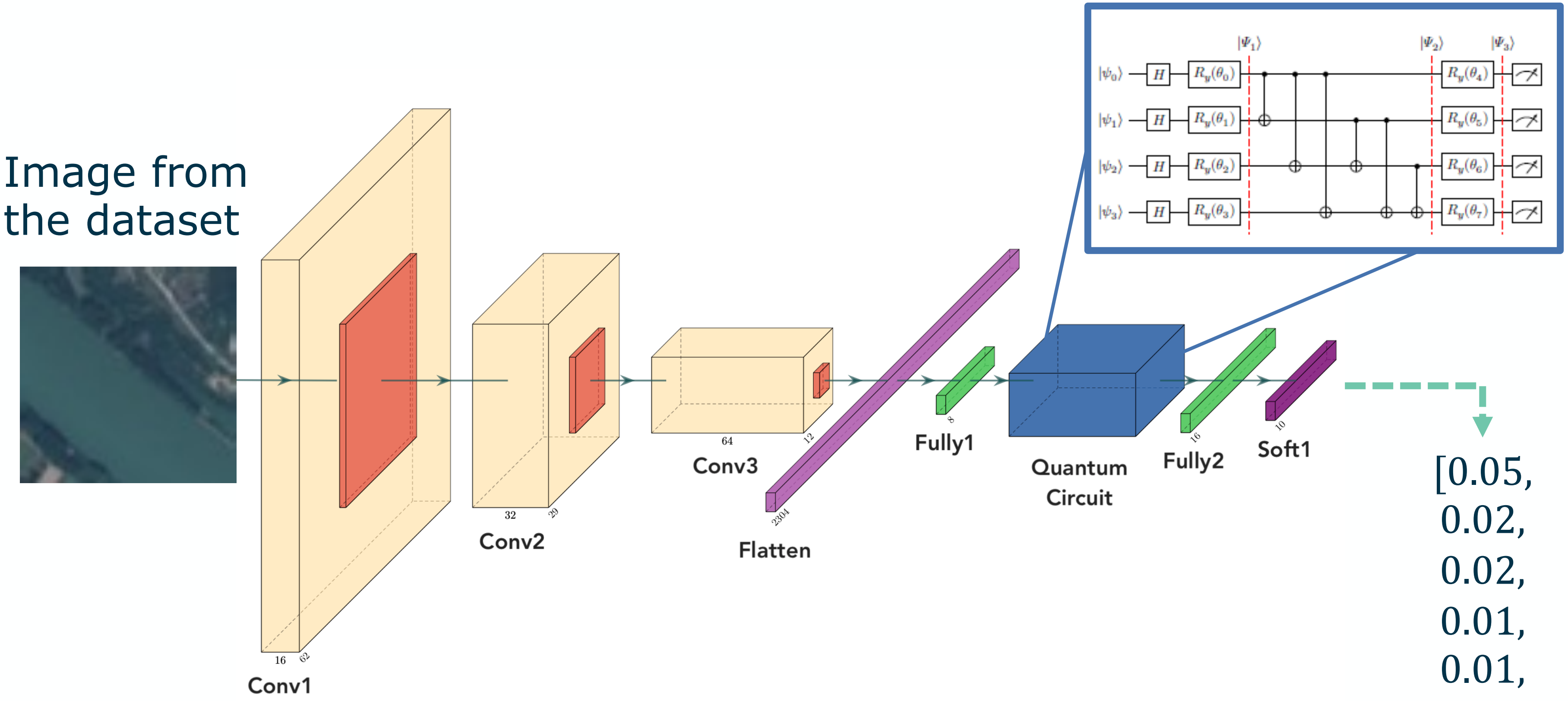
- Forward Pass



Training [2]

- Forward Pass
- Loss Calculation

Image from the dataset



[0.05, 0.02, 0.02, 0.01, 0.01, 0.02, 0.01, 0.01, 0.05, 0.98]

Predicted Label $\hat{y}$

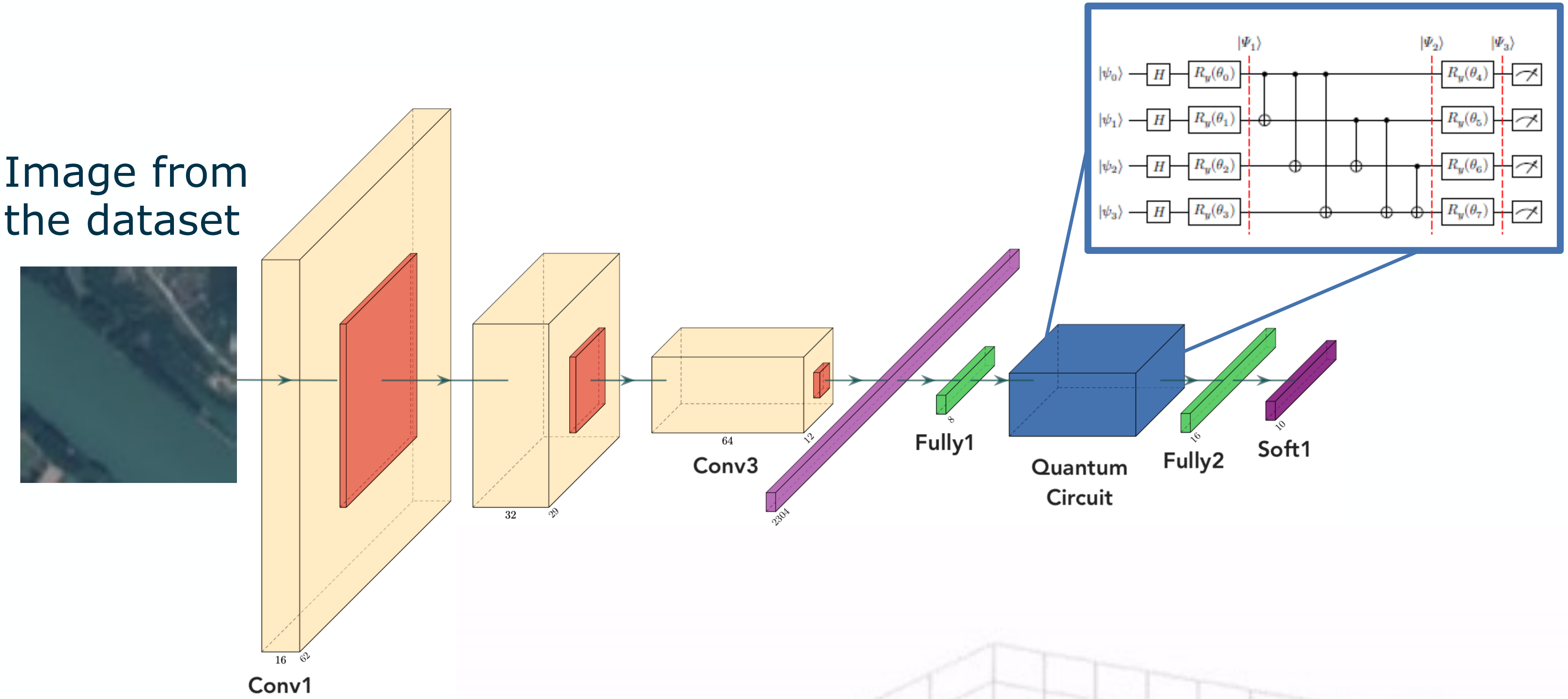
Loss=$-\sum_{i=1}^{10} y_i \cdot \log \hat{y}_i$

Image Label River y

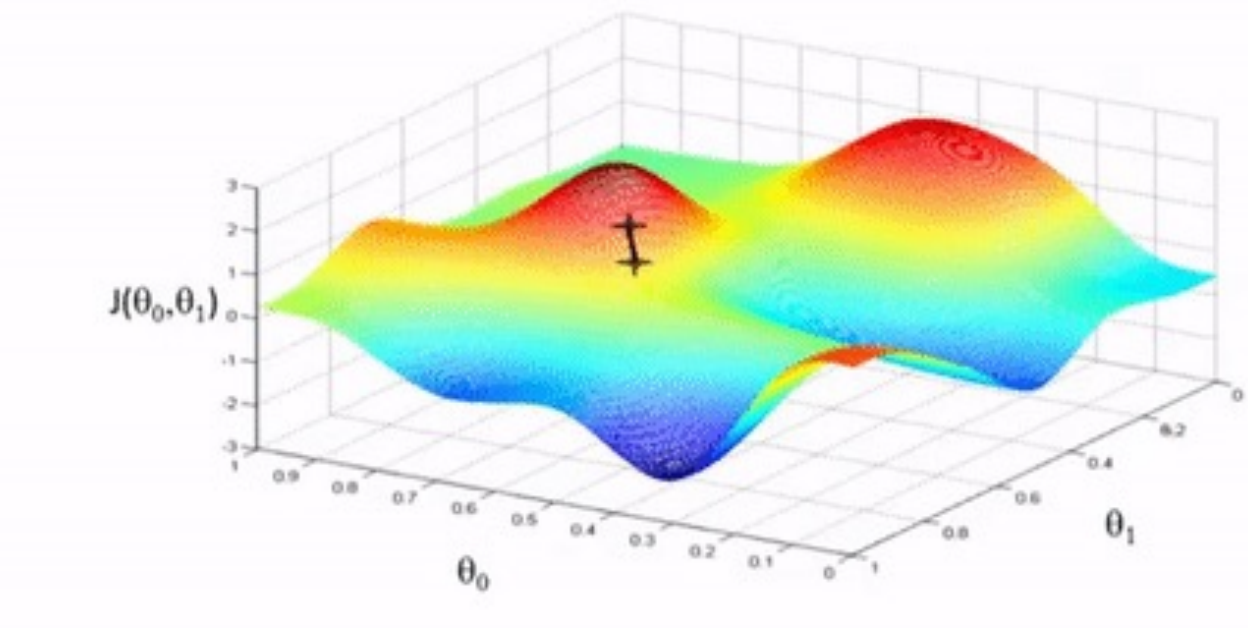
[0., 0., 0., 0., 0., 0., 0., 0., 0., 1.]

Training [3]

- Forward Pass
- Loss Calculation
- **Backward Pass**



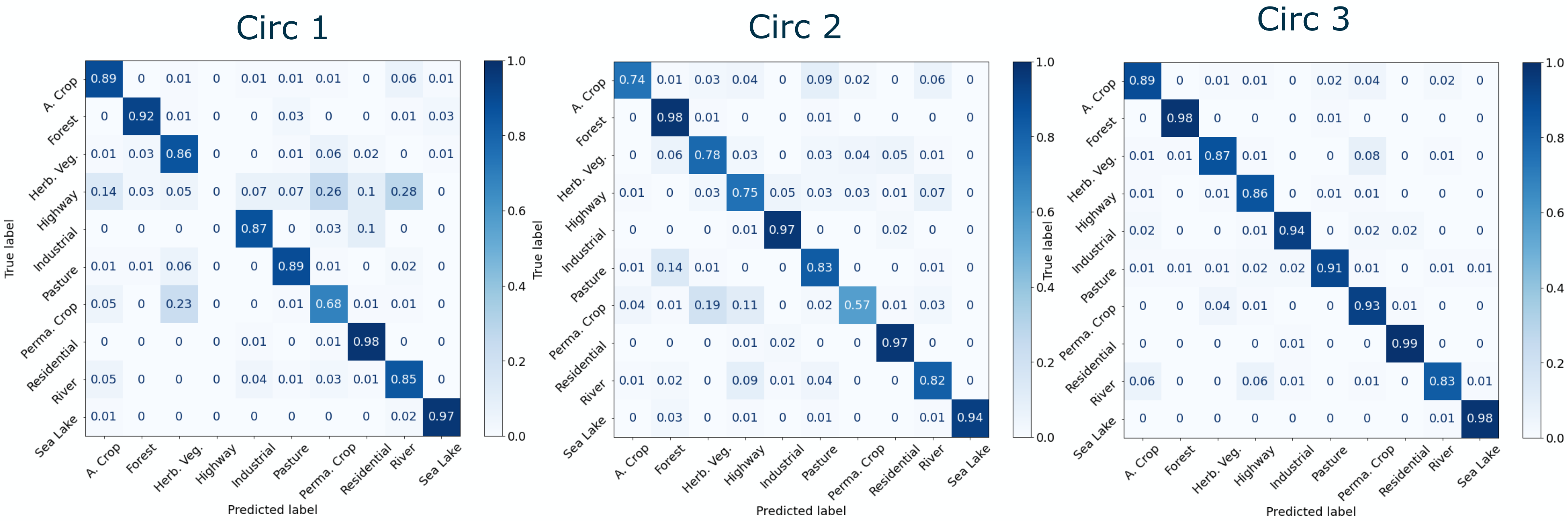
Both classical and quantum weights are updated



RESULTS

Results [1]

- Classification Results



A confusion matrix is a technique for summarizing the performance of a classification algorithm.

Classification accuracy alone can be misleading if you have an unequal number of observations in each class or if you have more than two classes in your dataset.

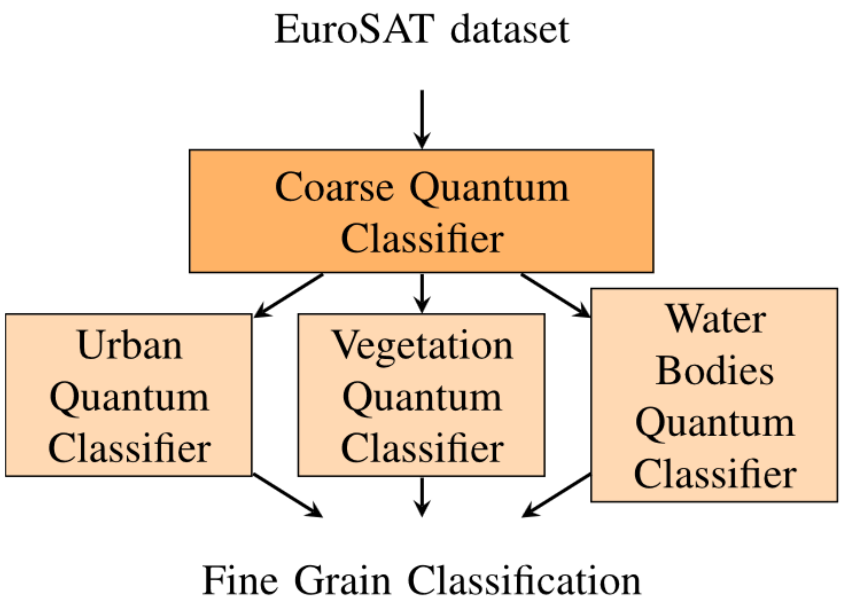
Calculating a confusion matrix can give you a better idea of what your classification model is getting right and what types of errors it is making

Results [2]

- Classification Results

Coarse-to-fine land-cover classifier

Class	Precision	Recall	F1 Score
Annual Crop	0.98	0.93	0.95
Permanent Crop	0.98	0.98	0.98
Pasture	0.93	0.94	0.94
Forest	0.95	0.95	0.95
Herbaceous Vegetation	0.93	0.94	0.94
Highway	0.99	0.99	0.99
Residential	0.99	0.99	0.99
Industrial	0.99	0.99	0.99
River	0.99	0.99	0.99
Sea Lake	0.99	0.99	0.99
Accuracy			0.97
Macro Average	0.97	0.97	0.97

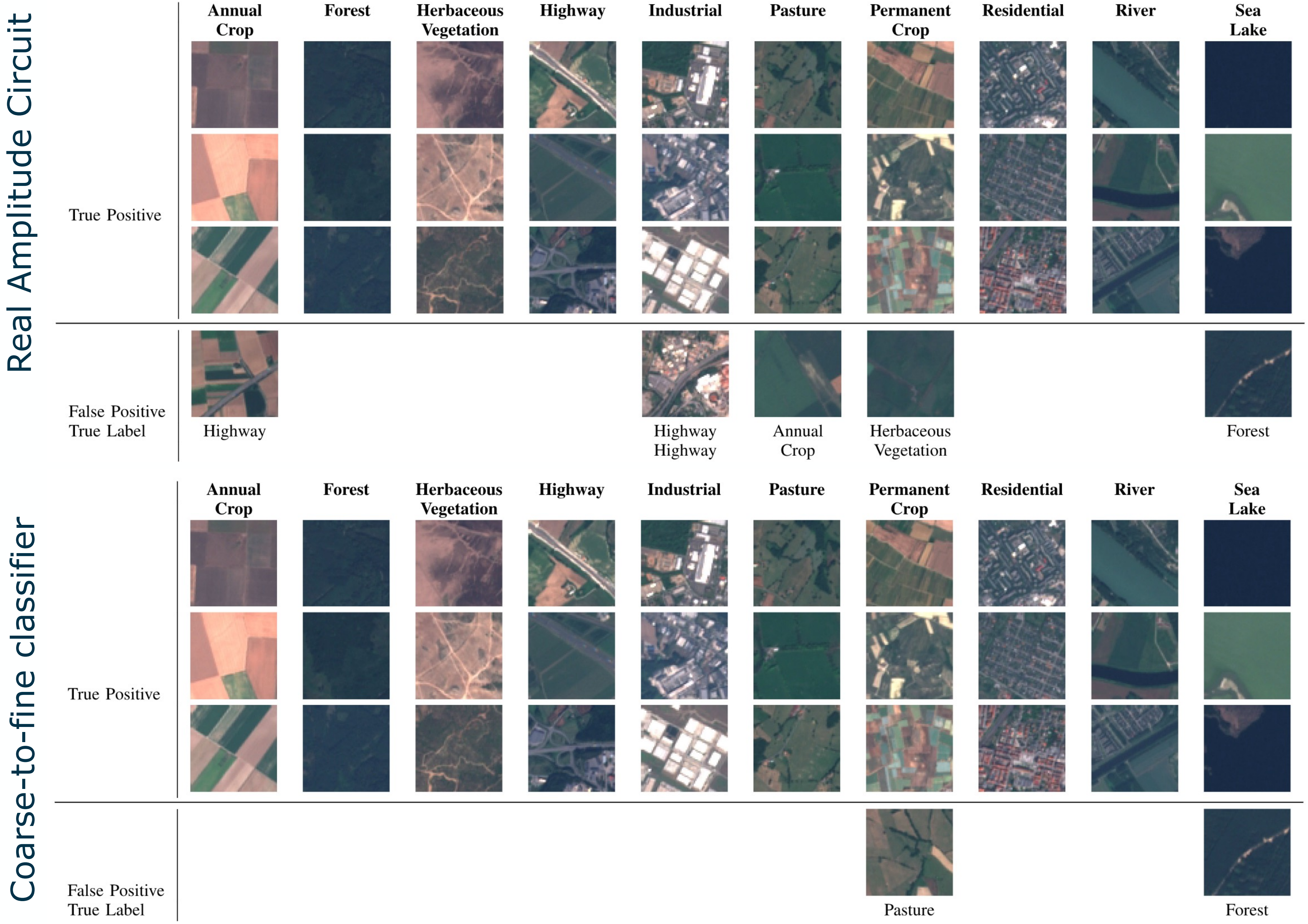


Comparisons with State of the Art

Model	Overall Accuracy	N. layers	N. parameters
Helber et Al. [35] ResNet-50	0.98	50	25.6M
Helber et Al. [35] GoogleNet	0.98	27	7M
Li et Al. [77] ResNet-18	0.98	18	11M
Sumbul et Al. [36] S-CNN-RGB	0.70	3	23.584
Classical V1	0.82	6	42.338
Classical V2	0.83	7	329.290
Circ 1	0.79	6	42.338 + 4q
Circ 2	0.84	6	42.338 + 4q
Circ 3	0.92	6	42.338 + 8q
Fine land-cover classifier	0.97	6	42.338 + 8q

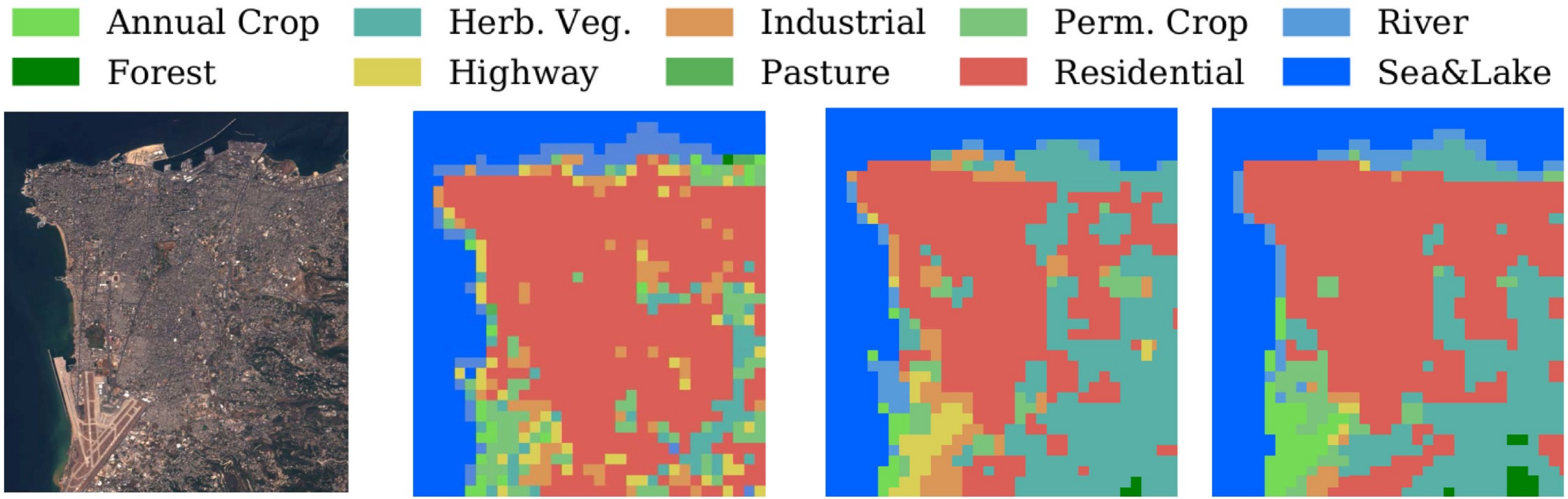
Results [3]

- Classification Results

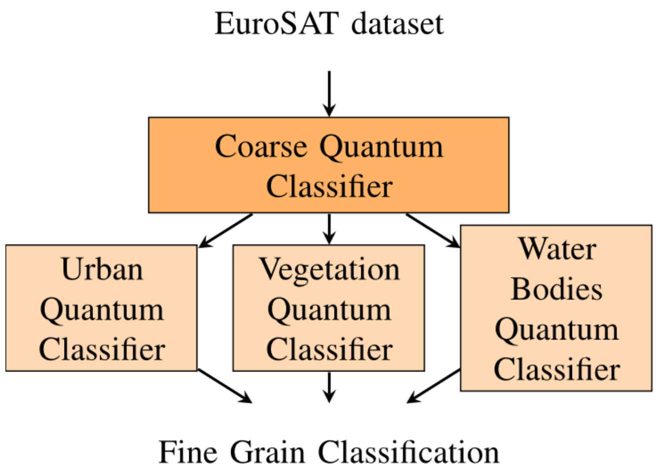


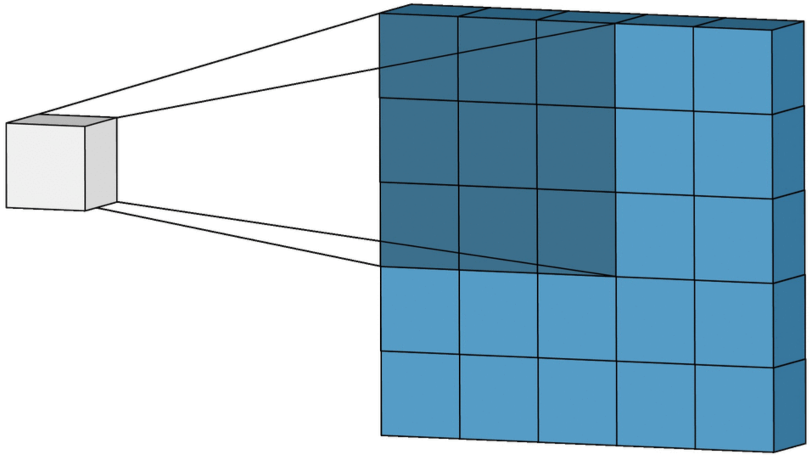
Results [4]

- Classification Results
- Segmentation Results



Sentinel-2 image | **coarse-to-fine quantum classifier** | **Wide-ResNet** | **JEM**





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- D. A. Zaidenberg, A. Sebastianelli, D. Spiller, B. Le Saux and S. L. Ullo, "Advantages and Bottlenecks of Quantum Machine Learning for Remote Sensing," *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, Brussels, Belgium, 2021, pp. 5680-5683, doi: 10.1109/IGARSS47720.2021.9553133.
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- https://github.com/alessandrosebastianelli/QAI4EO
- https://github.com/alessandrosebastianelli/hybrid-quantum-classifier