Quantum Machine Learning

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The world is how we shape it*

*Le monde est tel que nous le façonnons

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Agenda

01 Introduction

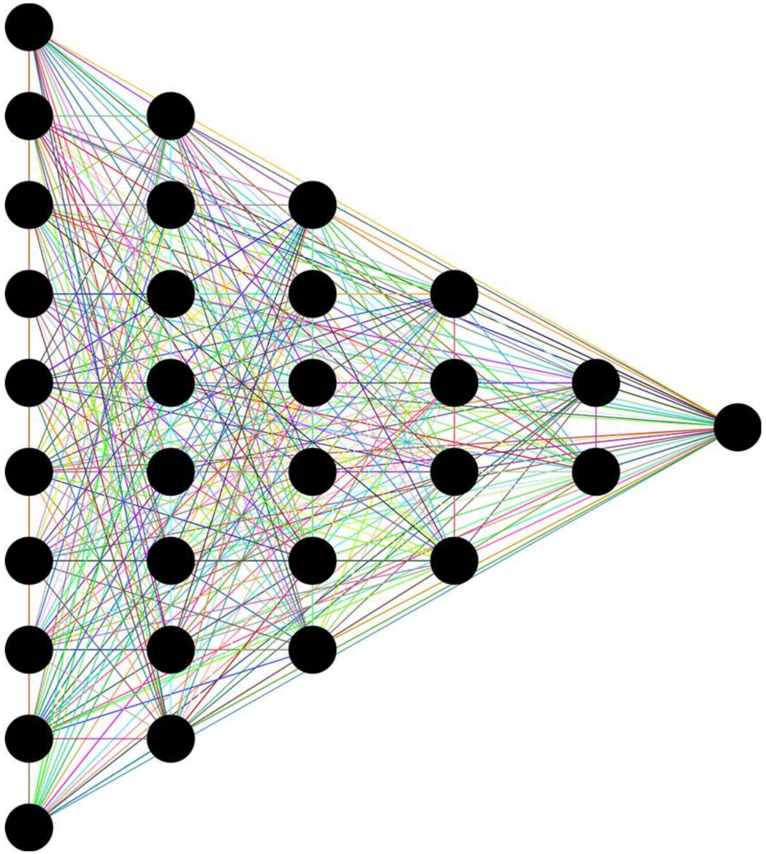
02 Ising Model Algorithm

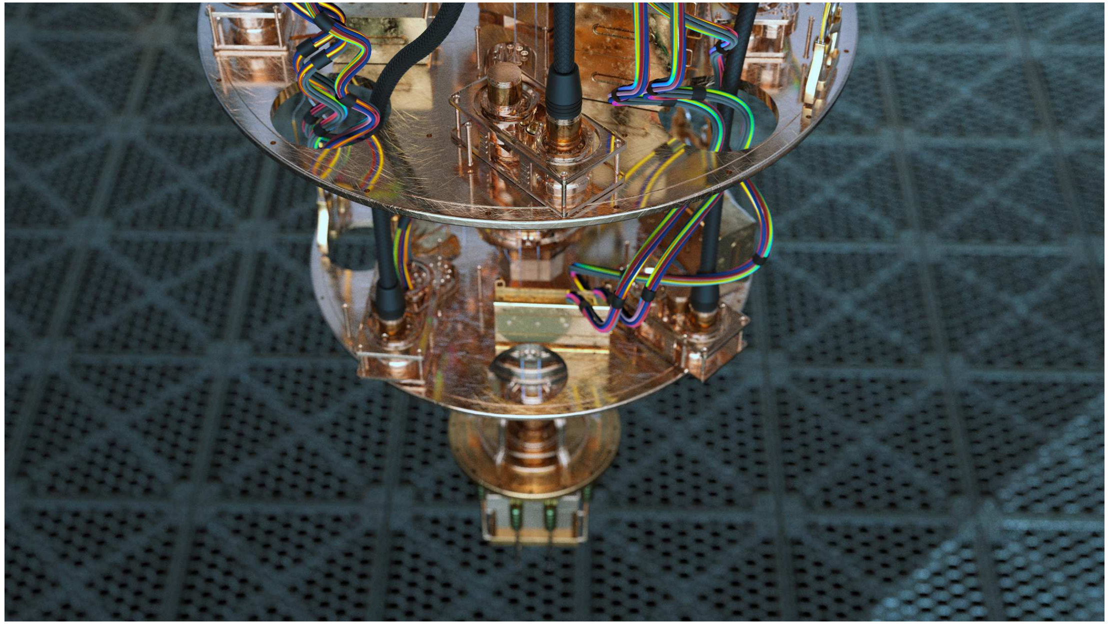
03 Conclusion

Agenda

Introduction

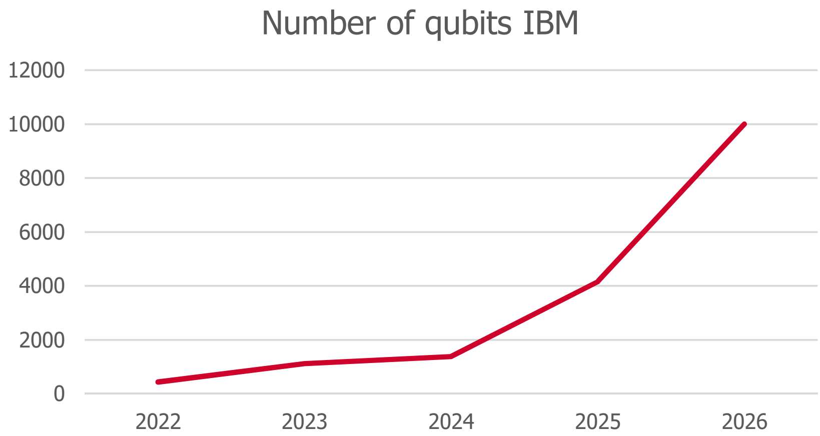
Machine Learning and Quantum Computing

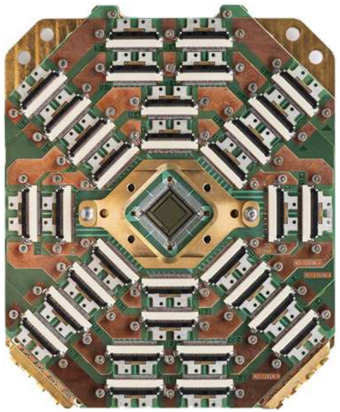




Quantum Computers

- The computer vendors have an ambitious roadmap





- D-Wave plans a quantum annealer of 7000 qubits in 2024
- Rigetti plans a gate-based system of 1000 qubits in 2026 and 4000 qubits in 2027
- European Commission supports projects to 1000 qubits in 2027

Potential Advantages

- Improved Accuracy
- Quantum Speedup
- Reduced Energy Usage

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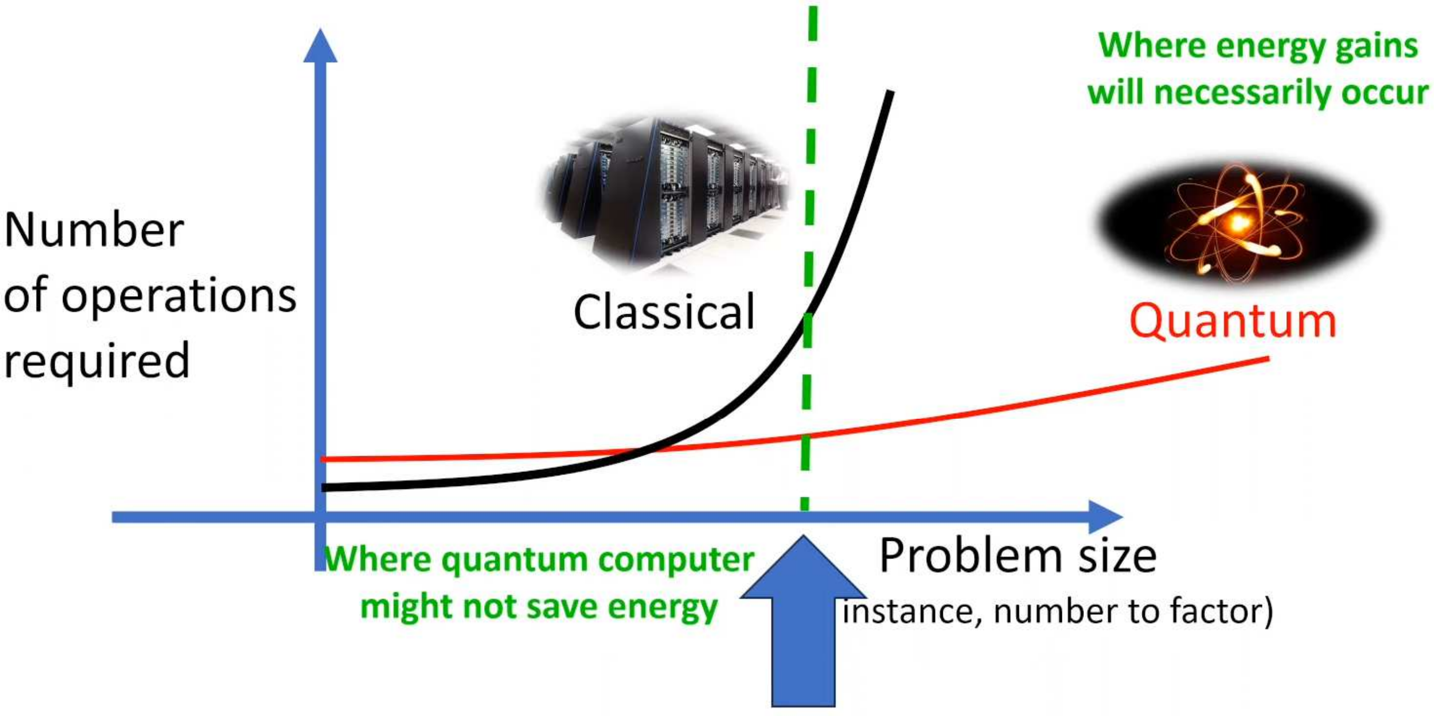
Reduced energy usage



We need to find **where** the transition occurs

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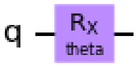
Quantum computing basics

- A **qubit** is a quantum system with two levels

  $\alpha\ |0> + \beta\ |1>$

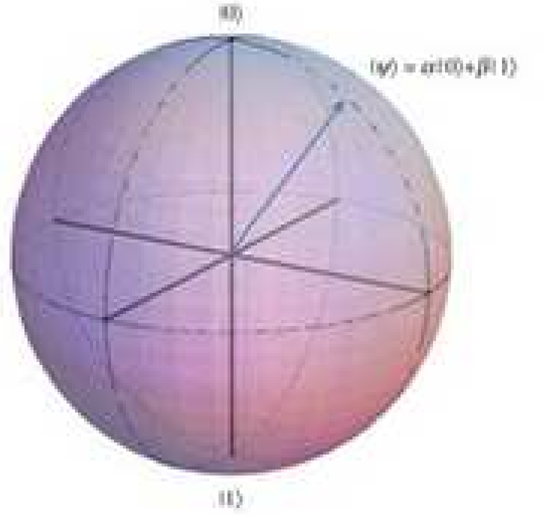
  and we observe $P(|0>) = |\alpha|^2$ and $P(|1>) = |\beta|^2$

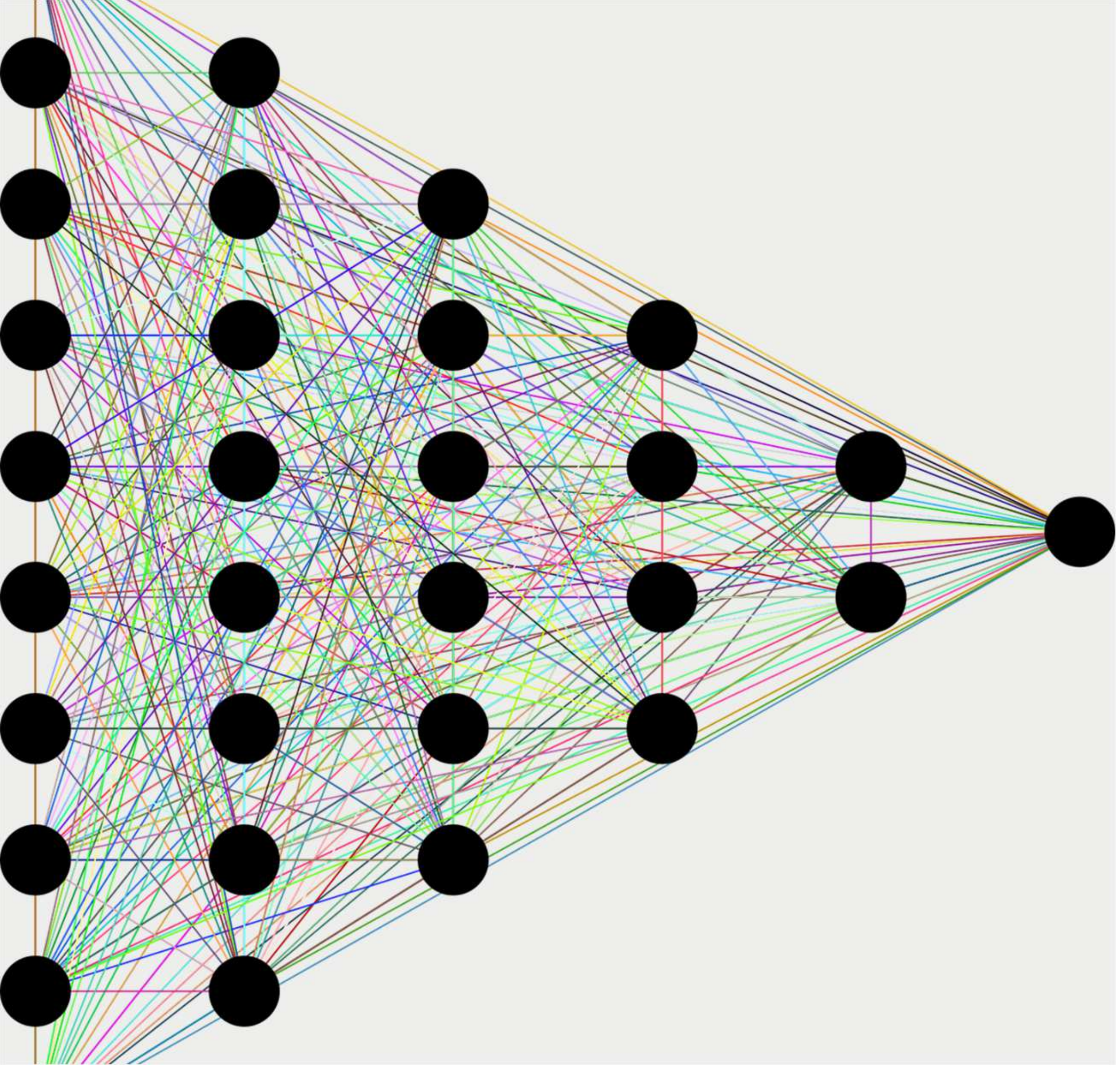
- A **quantum circuit** performs an operation on a qubit



- n **qubits** encode 2^n states in parallel.
  This is called **superposition**.

- 2 qubits can be **intricated**.





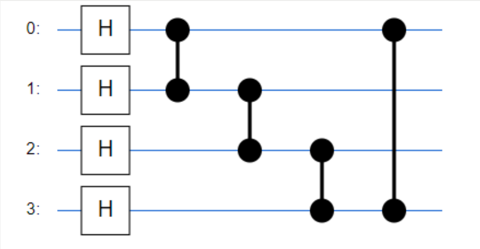
Quantum Neural Networks

Quantum Convolutional Neural Network

Quantum Layers and Classical Optimization

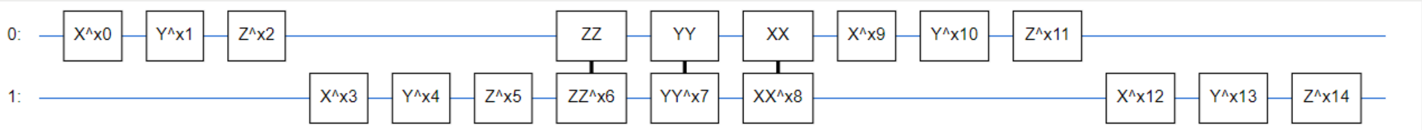
Data encoding

- Encoding of the images using a cluster state model



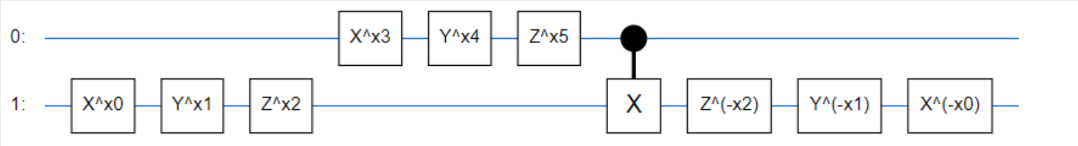
Quantum convolution

- Combine adjacent qubits with a convolution circuit



Quantum pooling

- Pool N qubits in N/2 qubits by reducing the intrication with a pooling circuit



Classical optimization

- TensorFlow functions

Scaling of feedforward time

- **Classical $O(N^2)$**
- **Quantum $O(N)$**

Ref: *M. van Waveren et al*, Comparison of Quantum Neural Network Algorithms for Earth Observation Data Classification, *Proceedings of IGARSS 23, Pasadena, California, 2023*.

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Other quantum neural network algorithms

- **Quantum Contrastive Learning Algorithm**

Ref: *V. Defonte et al*, Quantum Contrastive Learning for Semantic Segmentation of Remote Sensing Images, *Proceedings of Big Data from Space 23, Vienna, 2023*.

- **Quantum Long Short Term Memory Algorithm**

Ref: *H. Painchart et al*, Quantum Algorithm for the Analysis of Temporal Sequences of Satellite Images, *accepted at IGARRS 24, Athens, 2024*.

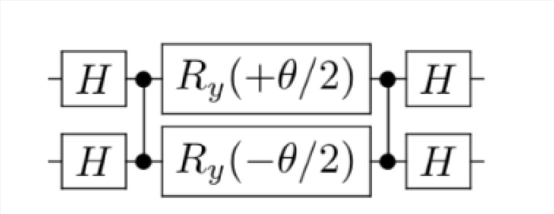
Orthogonal Neural Network

Neural network algorithm written as linear algebra operations with orthogonal weight matrices

Convert the linear algebra operations into quantum circuits

- Use the Reconfigurable Beam Splitter gate
- Define quantum pyramidal circuit with this gate
- Add data loader circuit

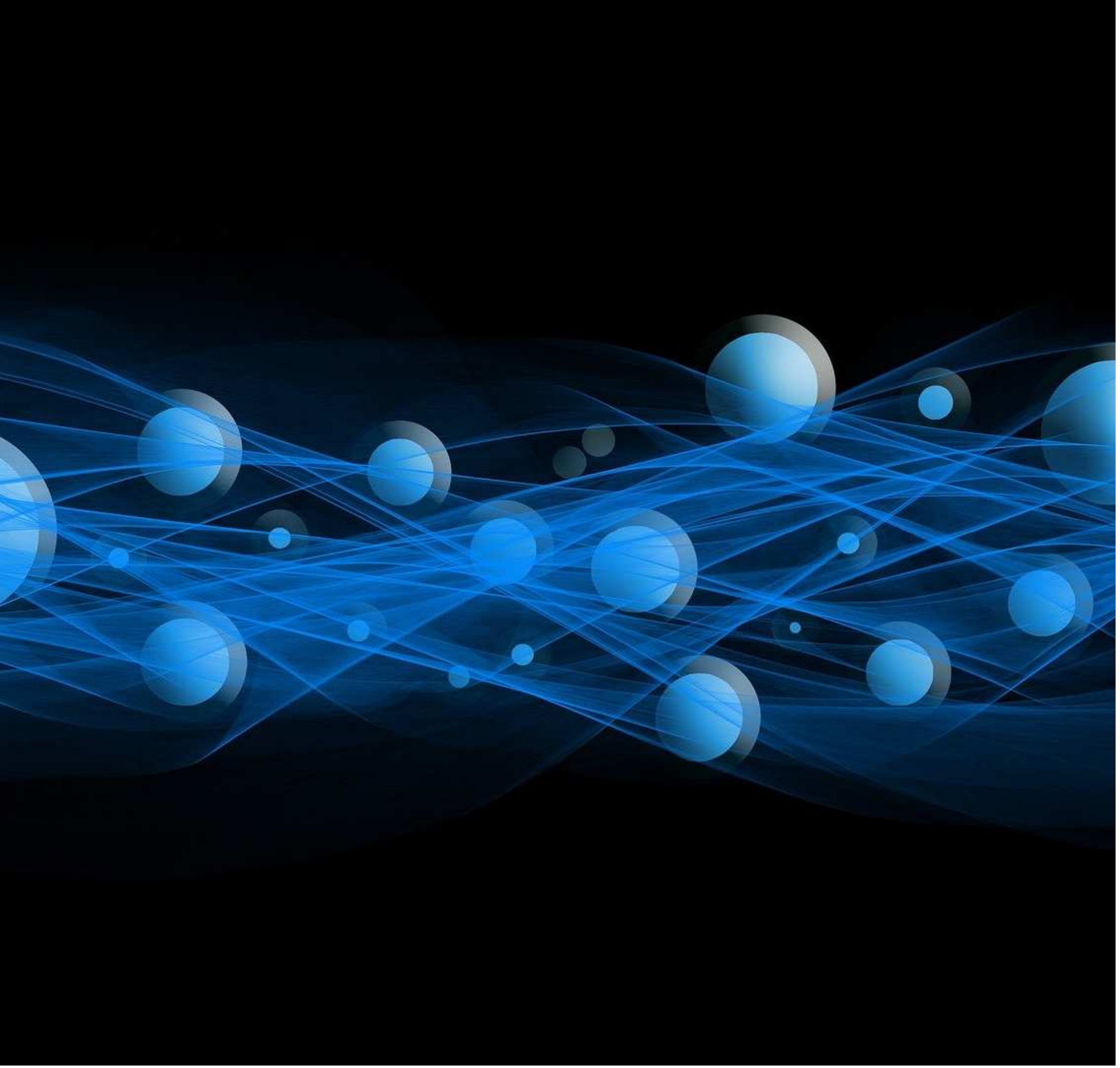
Can be executed either on quantum hardware or on classical hardware.



Scaling of feedforward time

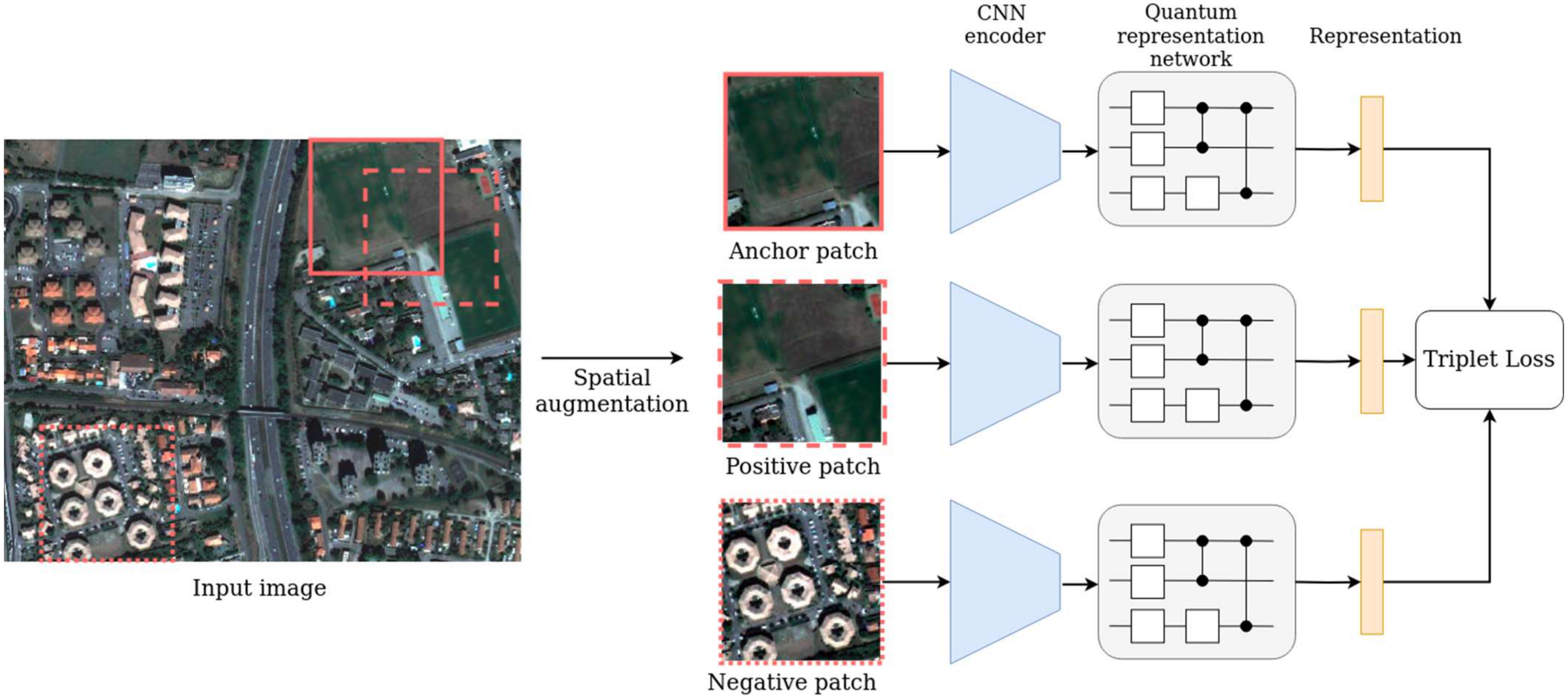
- Classical $O(N^2)$
- Quantum $O(N)$

Ref: *I. Kerinidis, J. Landman, N. Mathur*, Classical and Quantum Algorithms for Orthogonal Neural Networks, *https://arxiv.org/pdf/2106.07198*



Quantum Constrastive Learning

Hybrid Contrastive Learning Framework



Ref: *V. Defonte et al*, Quantum Contrastive Learning for Semantic Segmentation of Remote Sensing Images, *Proceedings of Big Data from Space 23, Vienna, 2023*.

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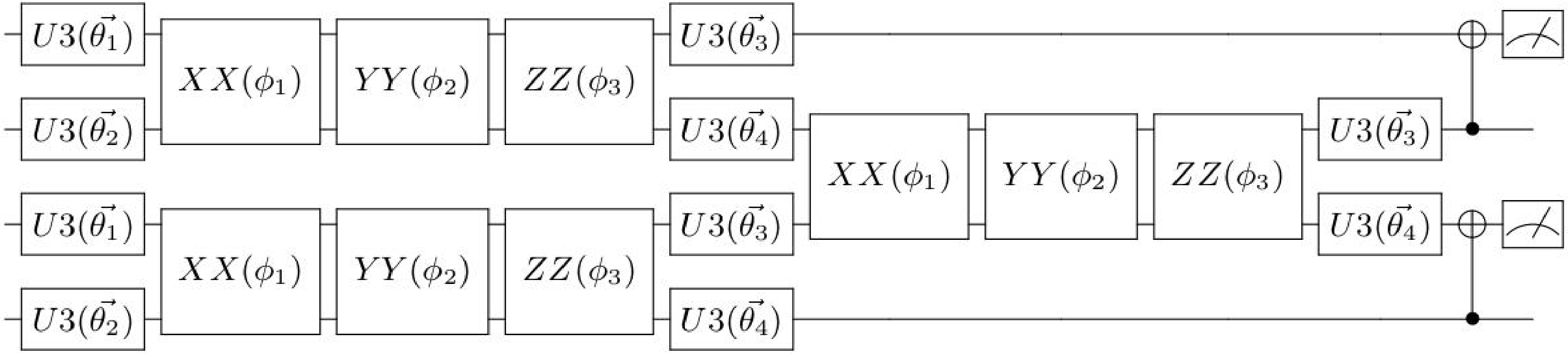
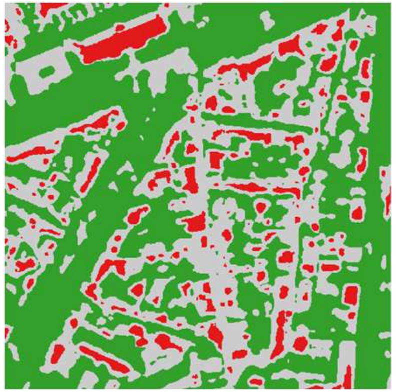
Parameterized Quantum Circuit



- 4-qubits version of the circuit from Cong et al
- Adapted to 8-qubits in this work
- Can be run on IBM quantum computer

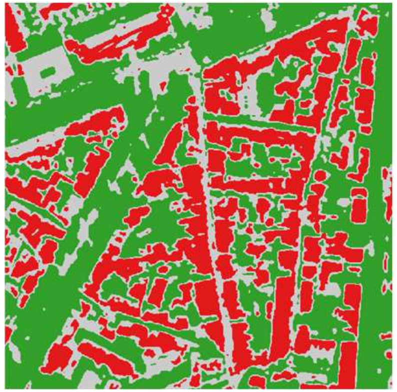
Results

RGB Image

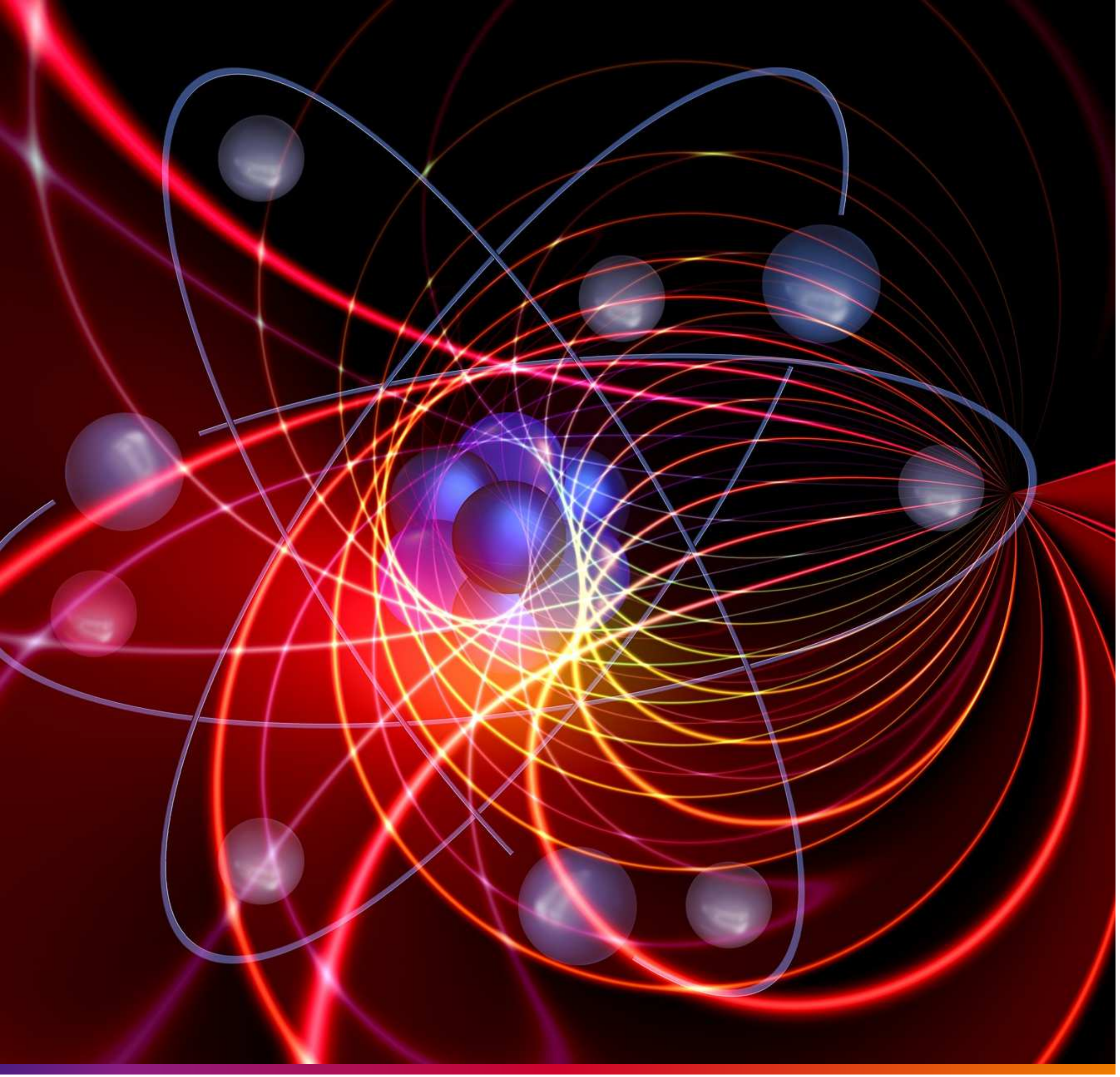


PCA

CNN

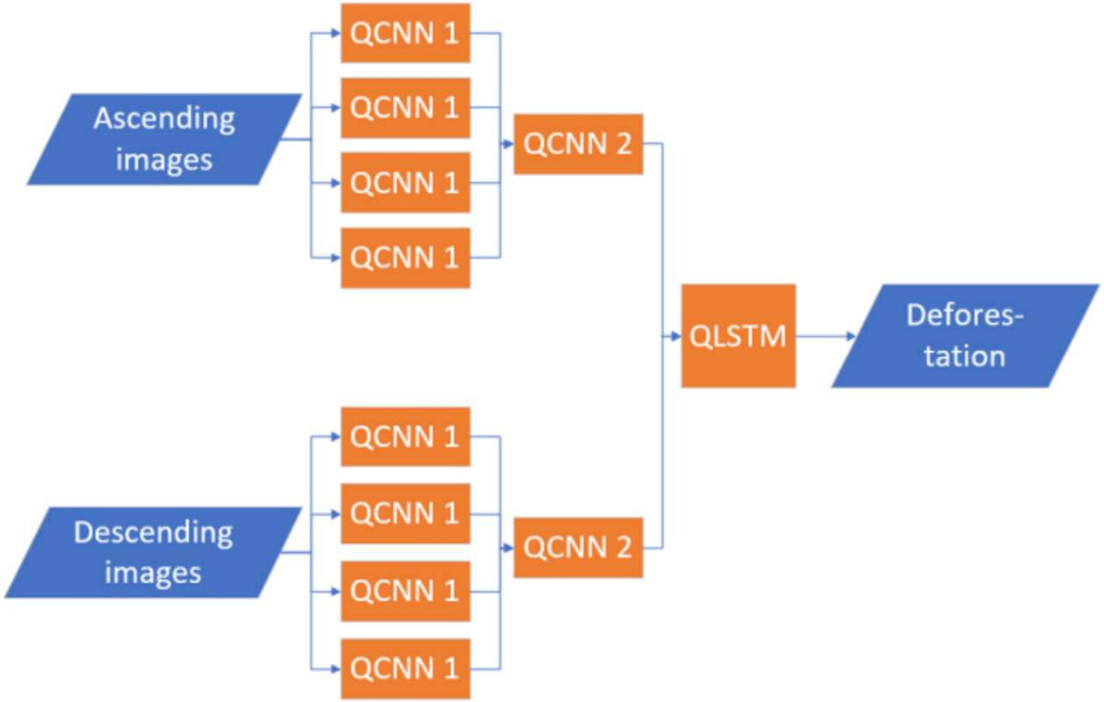


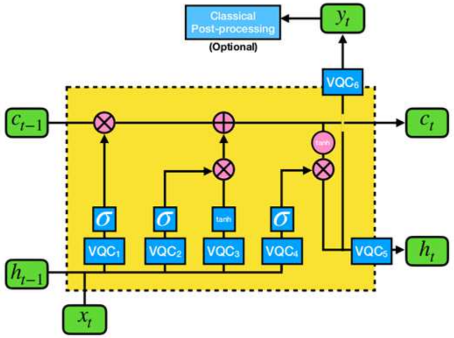
Hybrid

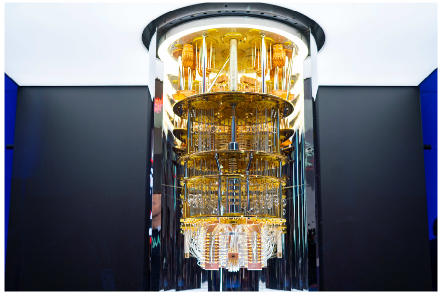


Quantum Long Short Term Memory

Method outline



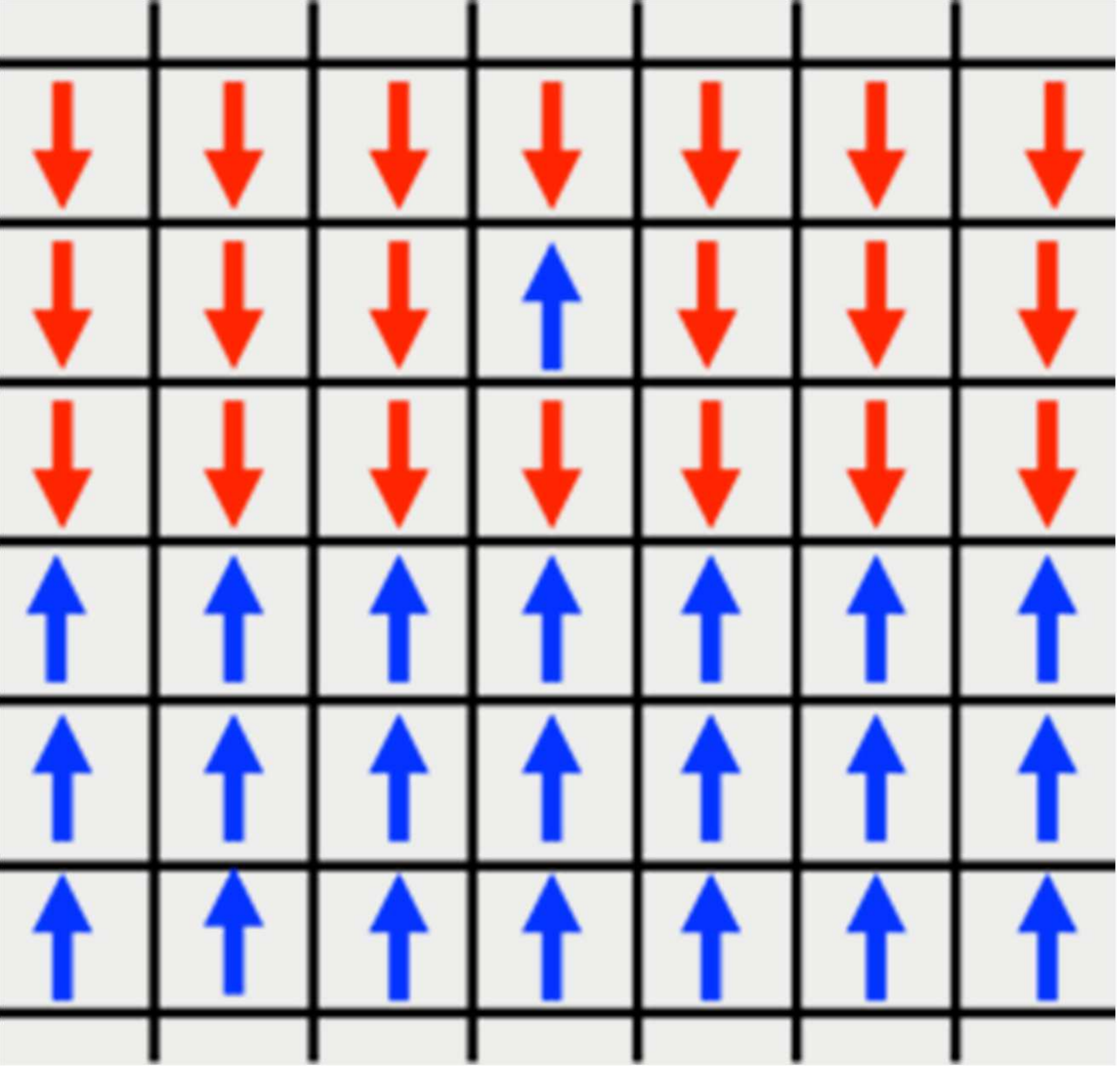




Ref: *H. Painchart et al*, Quantum Algorithm for the Analysis of Temporal Sequences of Satellite Images, *accepted at IGARRS 24, Athens, 2024*.

Model Accuracy Results

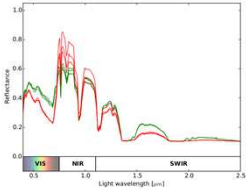
Phase	No iterations	Average Accuracy	Accuracy Stable Forest	Accuracy Deforestation
QCNN Ascending	20	76.5 %	87 %	67.3 %
QCNN Descending	20	75.2 %	79 %	71.6 %
QLSTM	100	76.5 %	52.9 %	100 %
Full Model	21	75 %	96.2 %	56.2 %
Final Model	11	81.3 %	85.7 %	75.7 %



Ising Model

Method outline

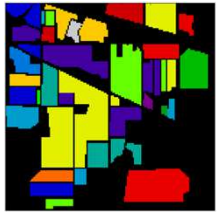
Indian Pines



Spectral information

Binary SVM for each class

training

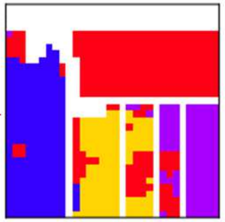


Training labels

Pixelwise per-class probability maps

Spatial information

Ising model on quantum annealer



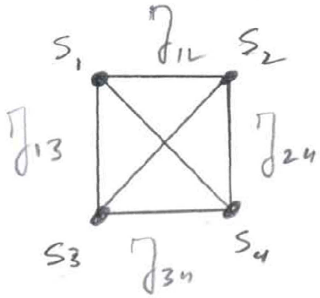
Predicted labels

Ref: *B. Gardas et al*, Hyper-spectral image classification using adiabatic quantum computation, *Proceedings of IGARSS 23, Pasadena, California, 2023*.

Ref: *P. Gawron et al*, What could be achieved with a Million qubits quantum annealer in Remote Sensing? *Accepted at IGARSS 24, Athens, Greece, 2024*.

Ising model

- Ising model is a random Markov field



- Image is mapped on a grid
- A local energy is associated with each pixel

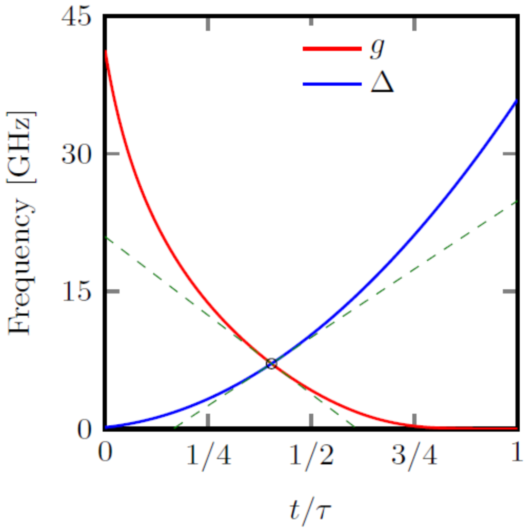
$$h_i = -\frac{1}{4}\log\left(\frac{1}{P_{i(c)}} - 1\right)$$

- A total energy is associated to the graph

One vs rest: $H(\boldsymbol{s}) = -\sum_i h_i s_i - \beta \sum_{ij} s_i s_j$

Potts model: $H(\boldsymbol{s}) = -\sum_i \sum_c h_{i,c} s_{i,c} - \beta \sum_{ij} s_{i,c1} s_{j,c2} - \gamma \sum_{i,c} (s_{i,c} + 2)^2$

Adiabatic Quantum Computing



- The D-Wave quantum annealer is used to solve the Ising model

$$H(t) = g(t)H_0 + \Delta(t)H_p$$

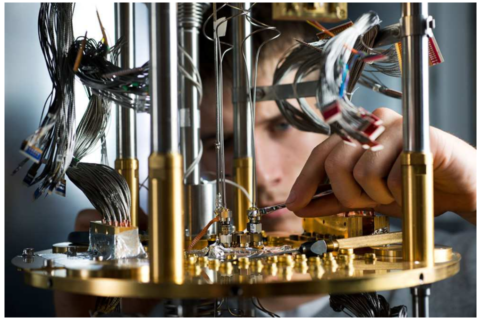
H_0 : Initial Hamiltonian of the quantum annealer
H_p : Hamiltonian corresponding to our problem

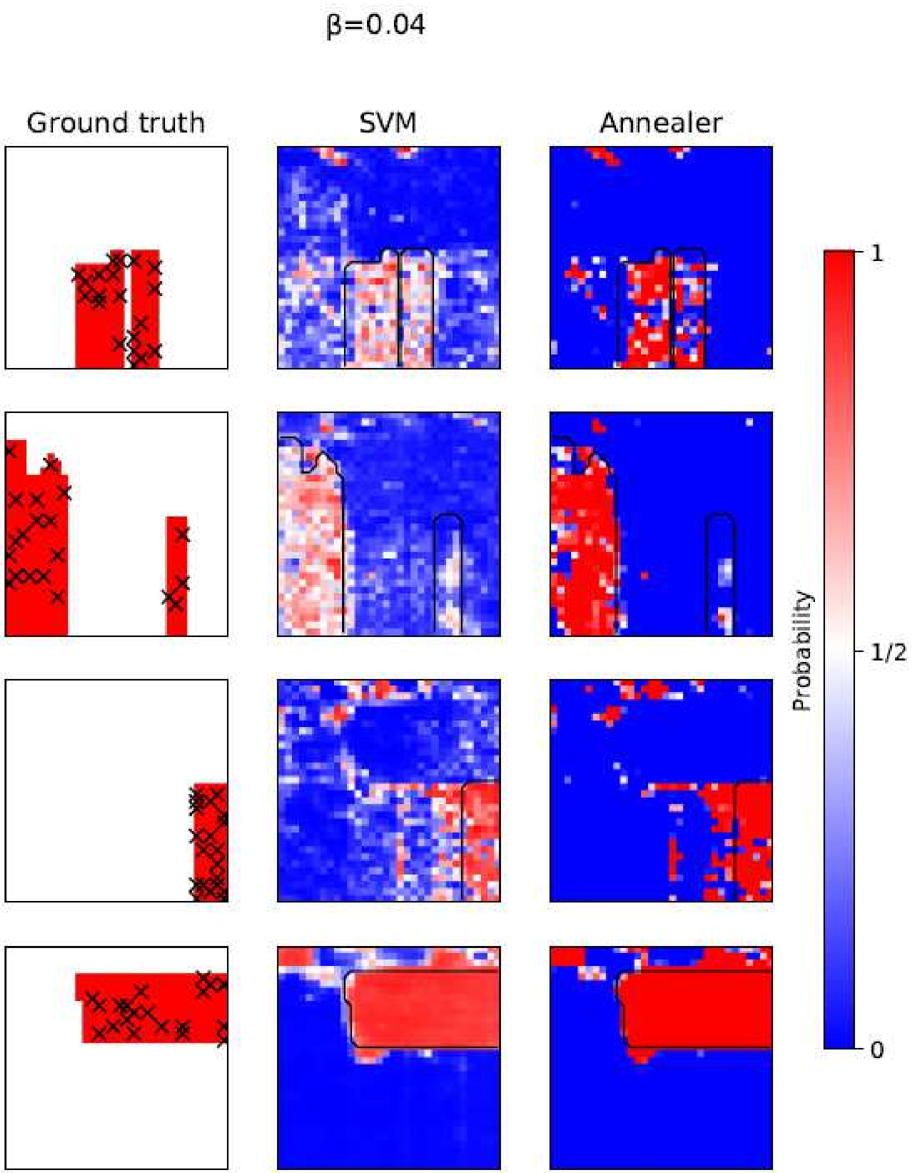
- If we start the computation in the ground state of H_0, then by varying $g(t)$ and $\Delta(t)$, we end up in the ground state of H_p for large annealing times.

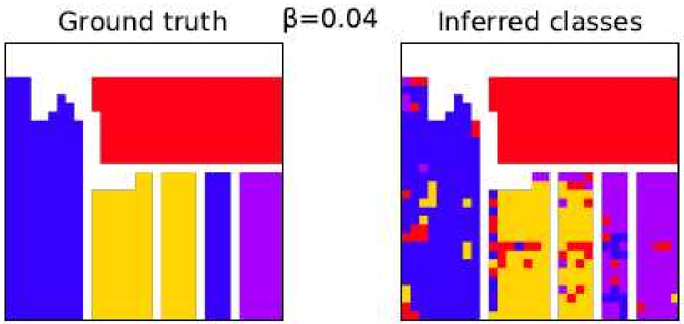
- The ground state of H_p corresponds to our solution.

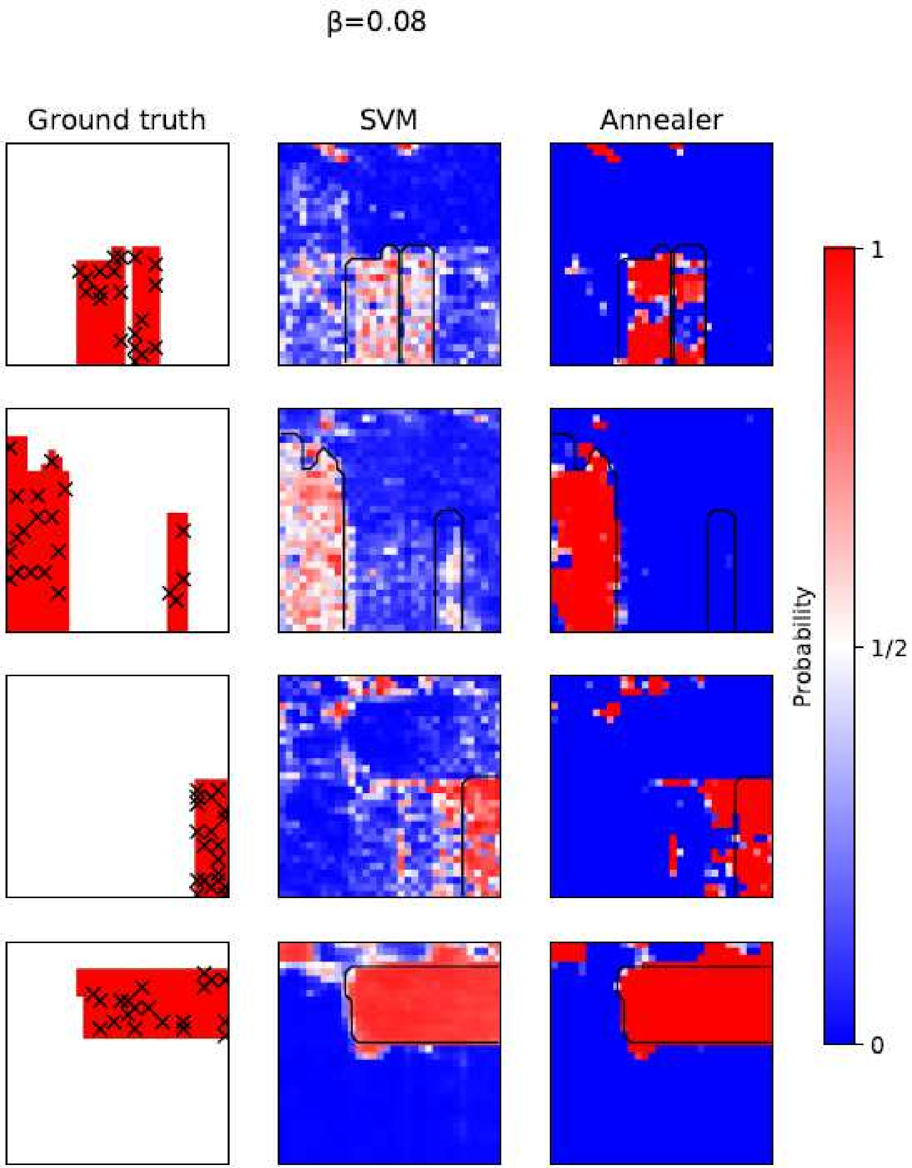
- Potts model results on D-Wave 2000-qubit system
  - Patch size: 8x8 pixels

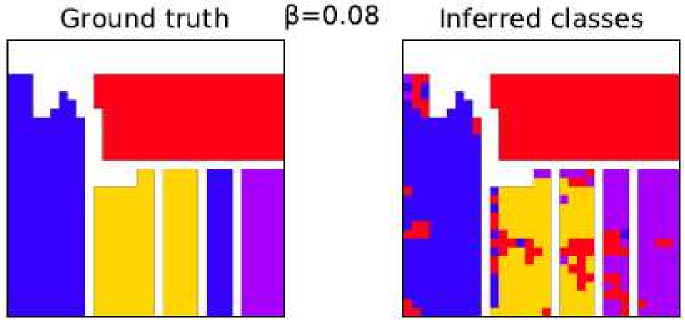
- Potts model results on D-Wave 5000-qubit Advantage system in Jülich
  - Patch size: 14x14 pixels

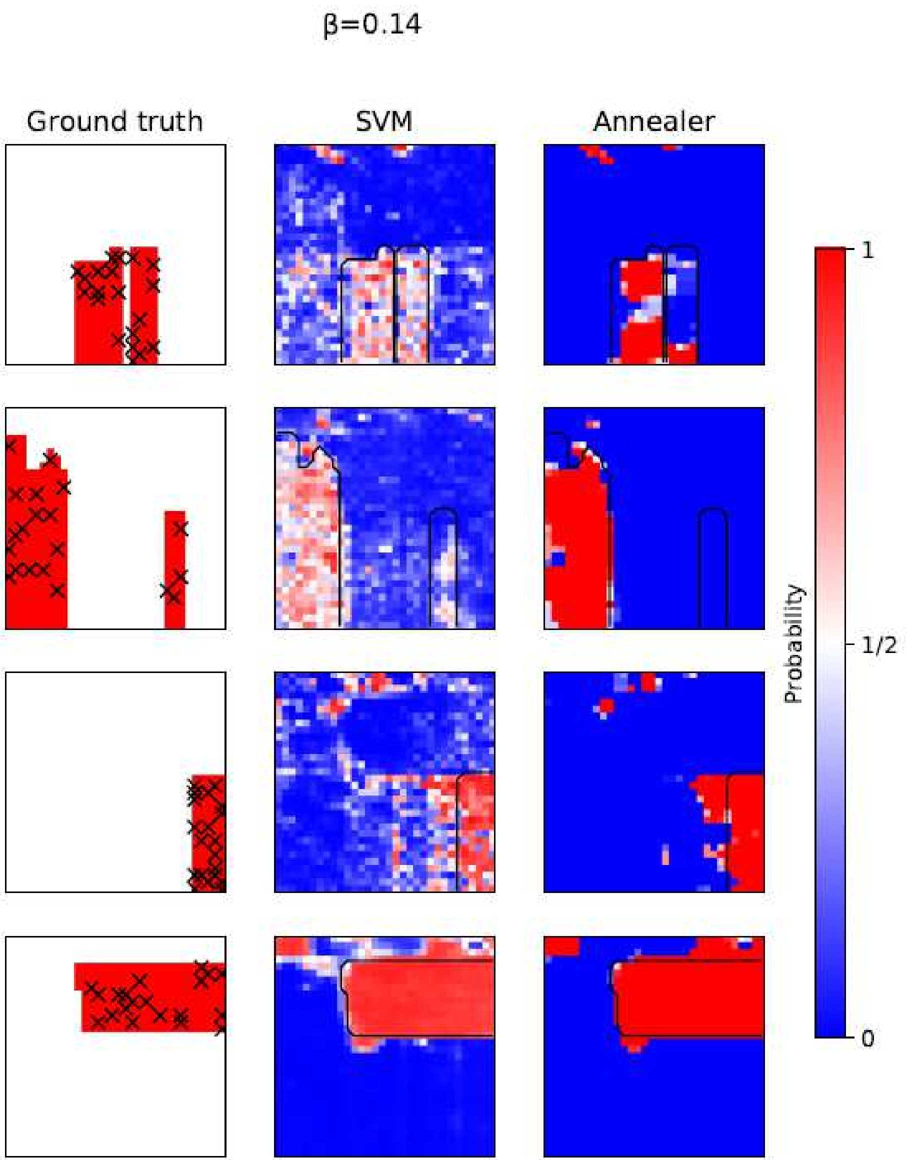


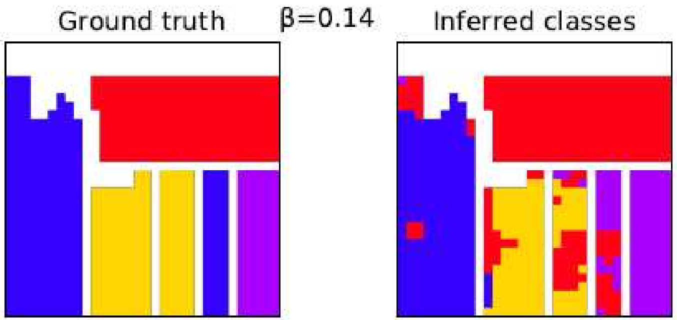

β=0.04
Ground truth
SVM
Annealer
Probability
1
1/2
0


Ground truth
β=0.04
Inferred classes

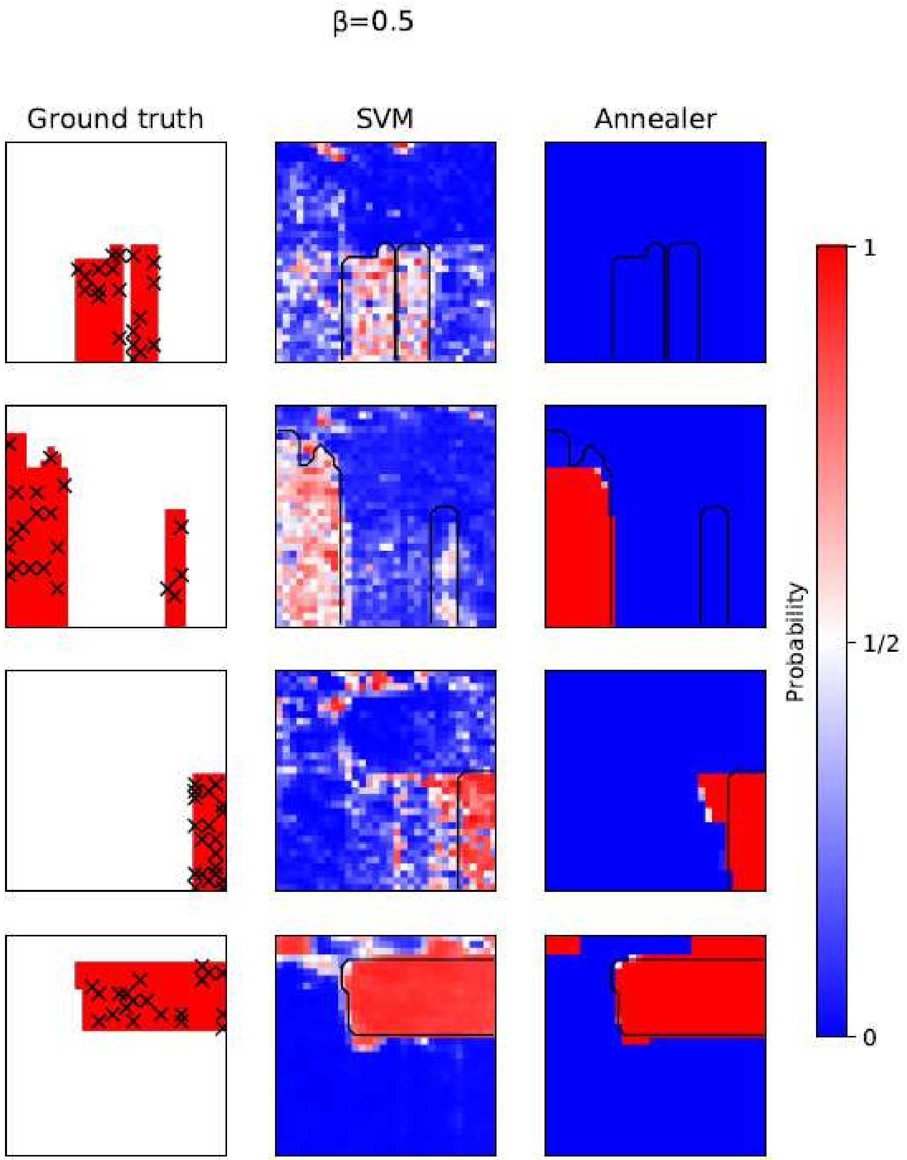

β=0.08
Ground truth
SVM
Annealer
Probability
1
1/2
0

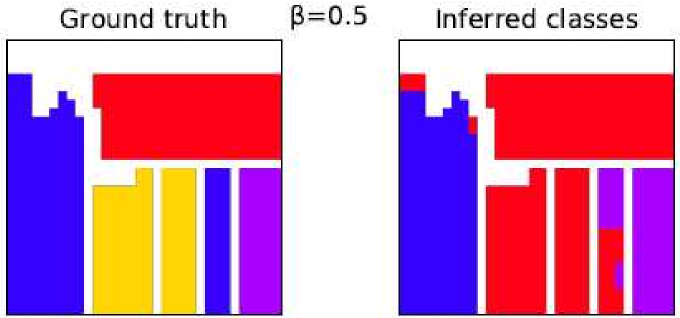

Ground truth
β=0.08
Inferred classes


β=0.14
Ground truth
SVM
Annealer
1
1/2
0
Probability

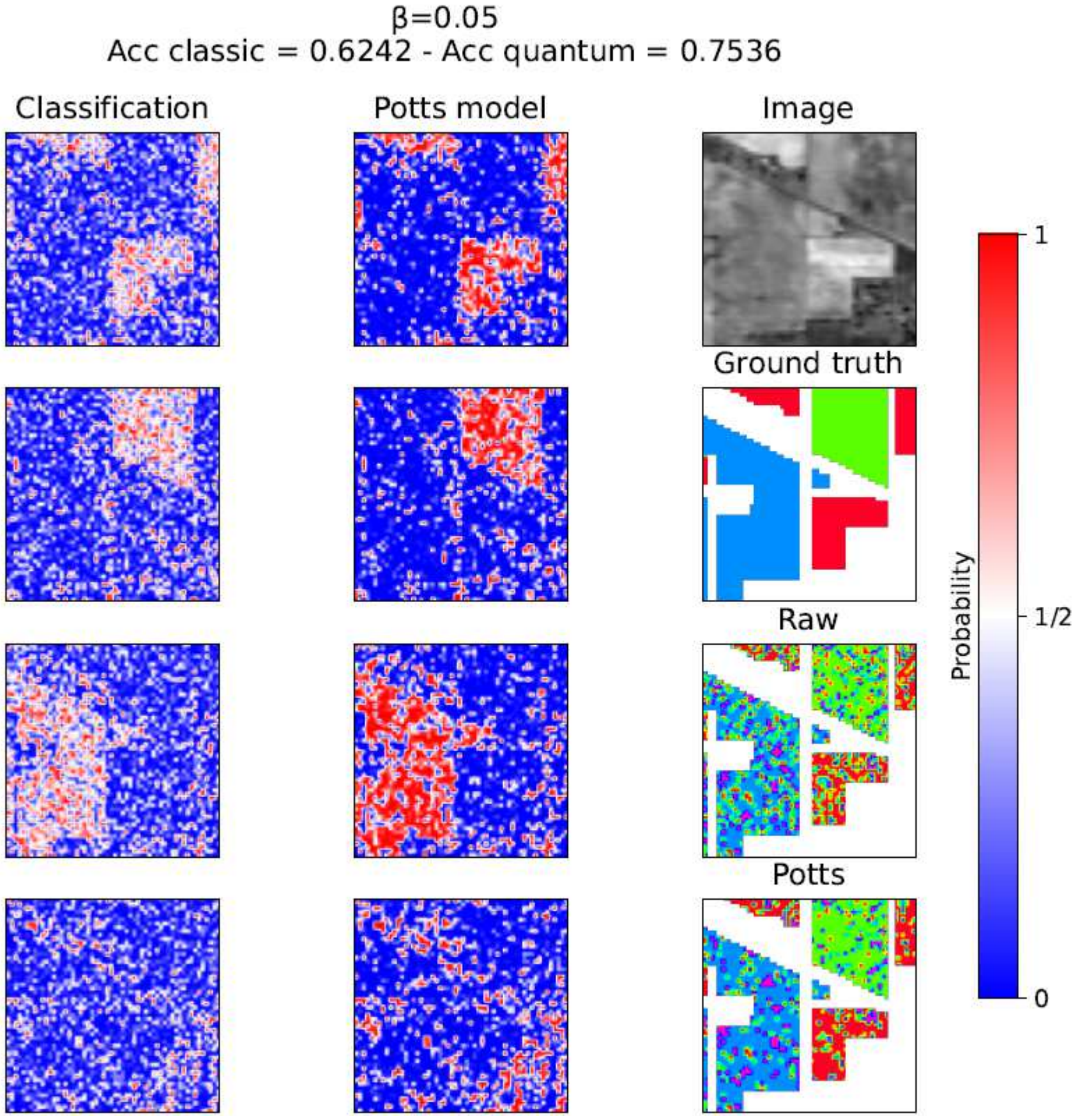

Ground truth
β=0.14
Inferred classes

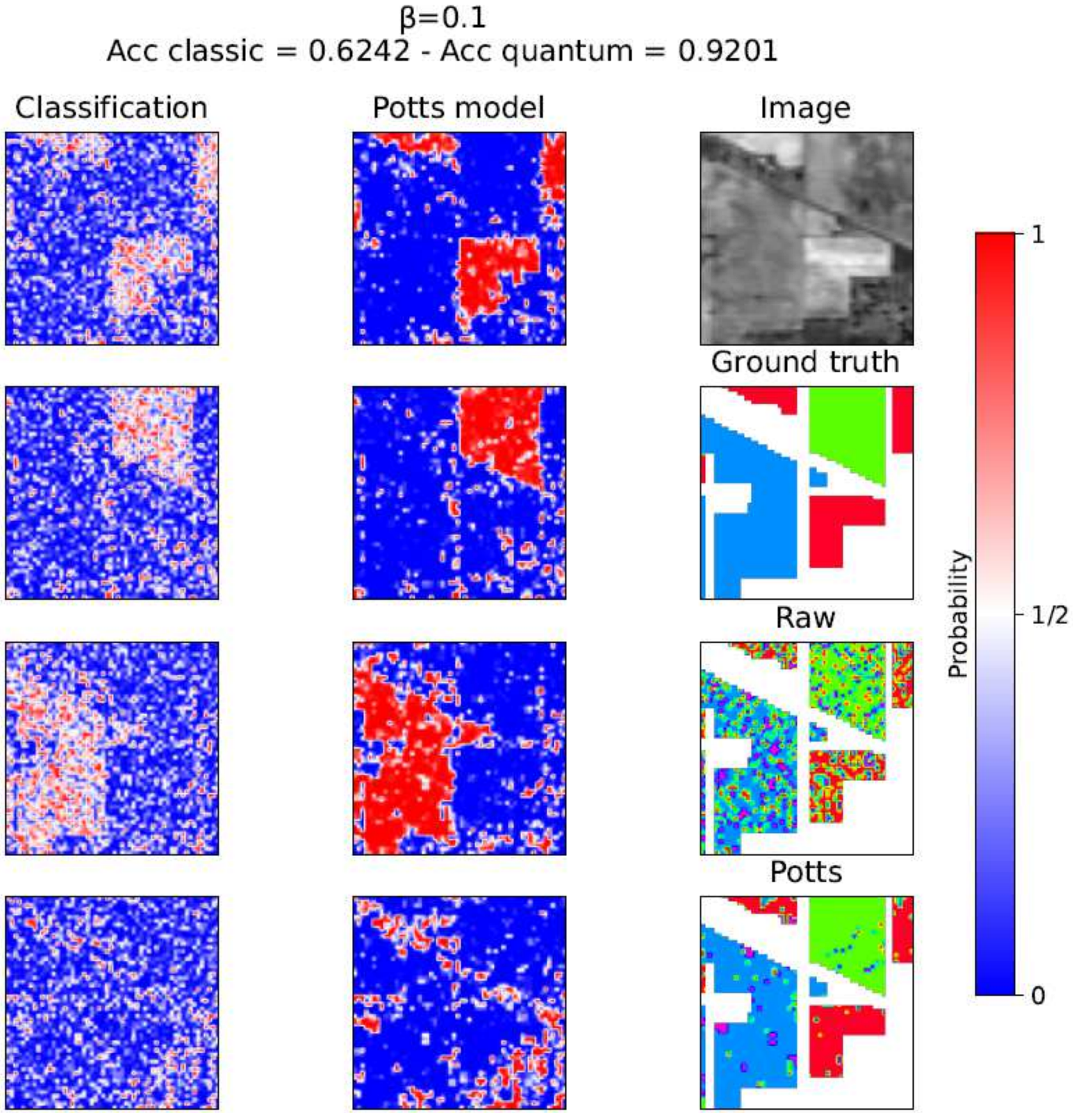
any


β=0.5
Ground truth
SVM
Annealer
Probability
1
1/2
0


Ground truth
β=0.5
Inferred classes

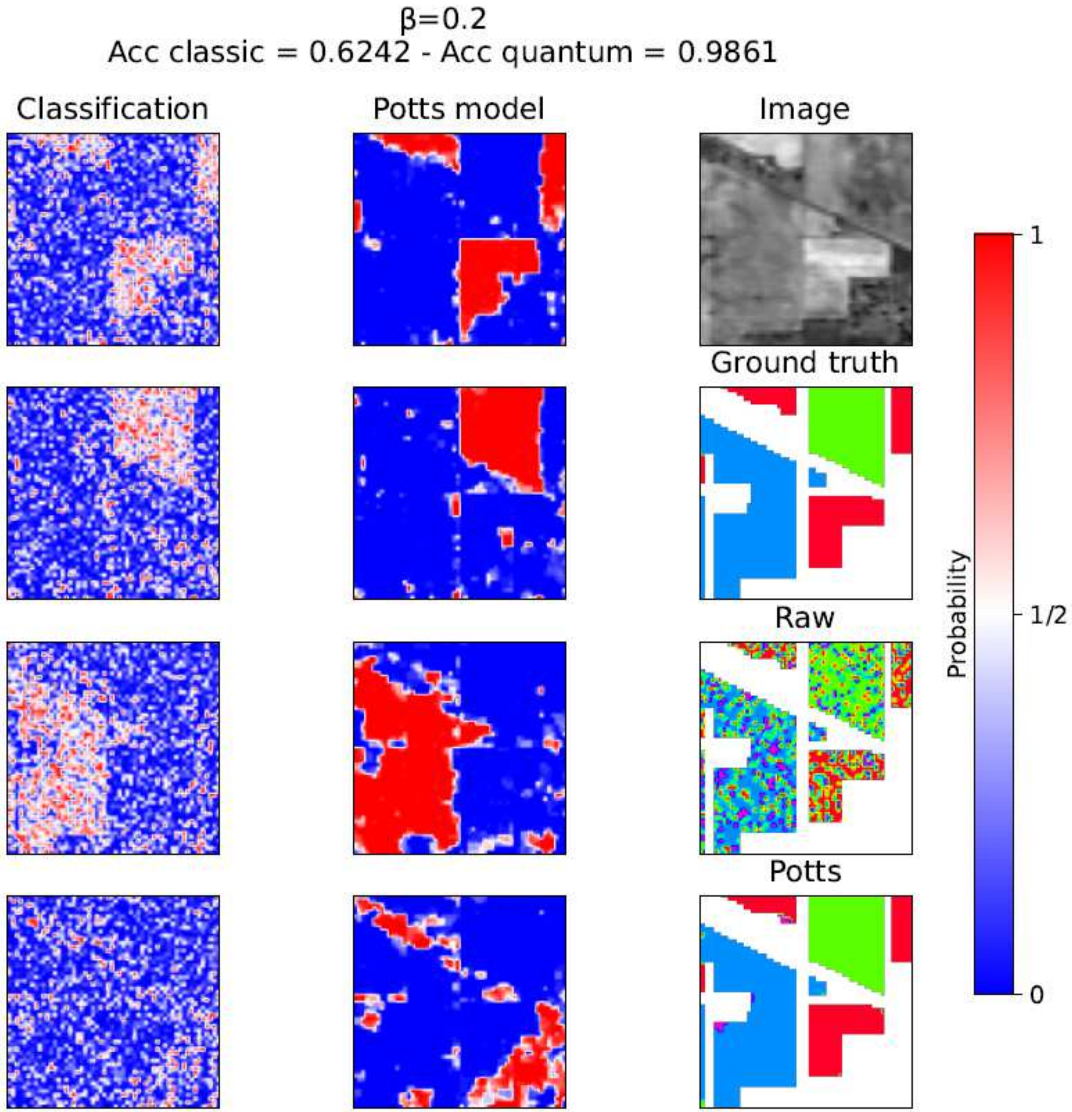
Ground truth with simulated noise



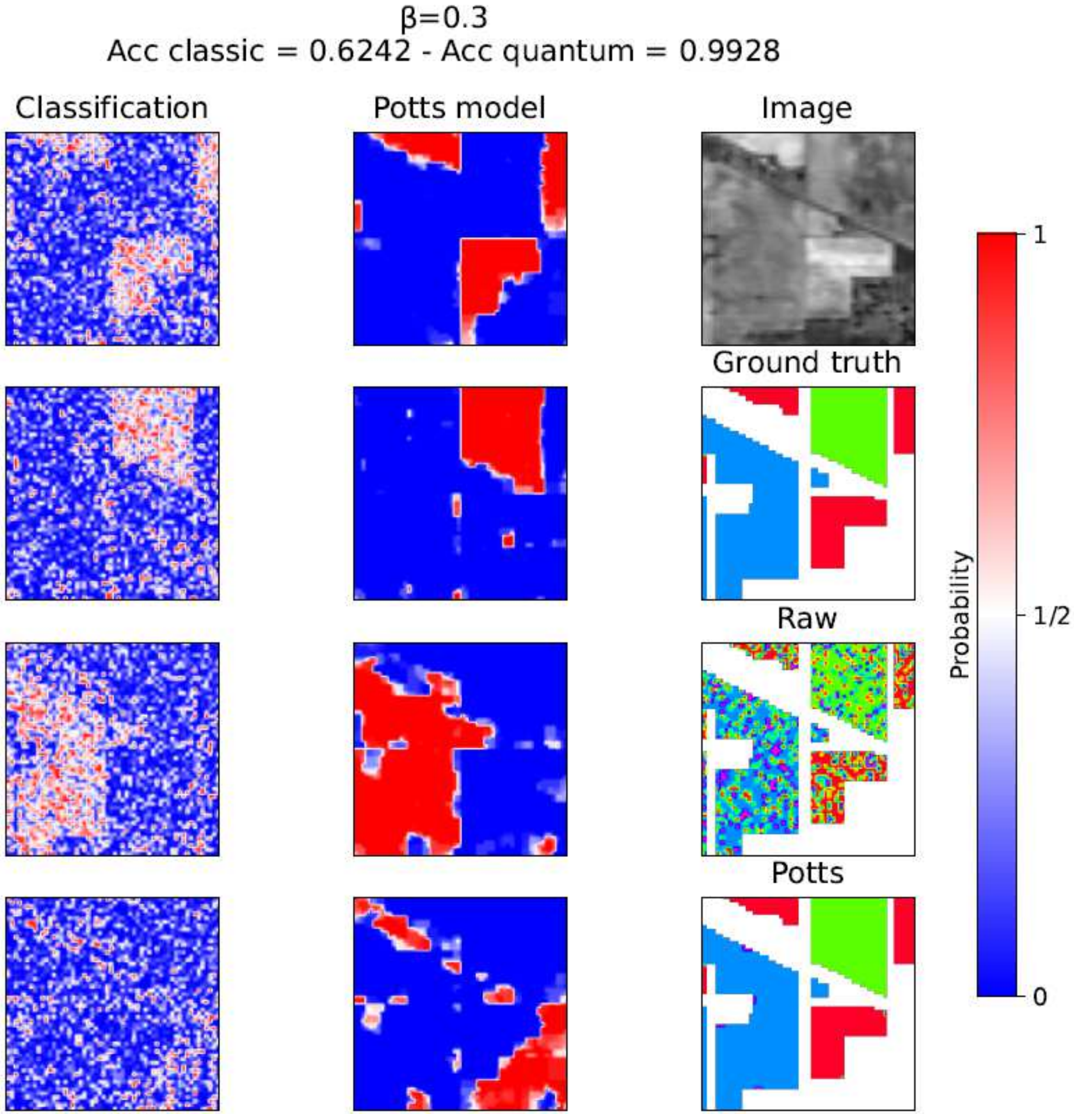


Ground truth with simulated noise

Ground truth with simulated noise



Ground truth with simulated noise



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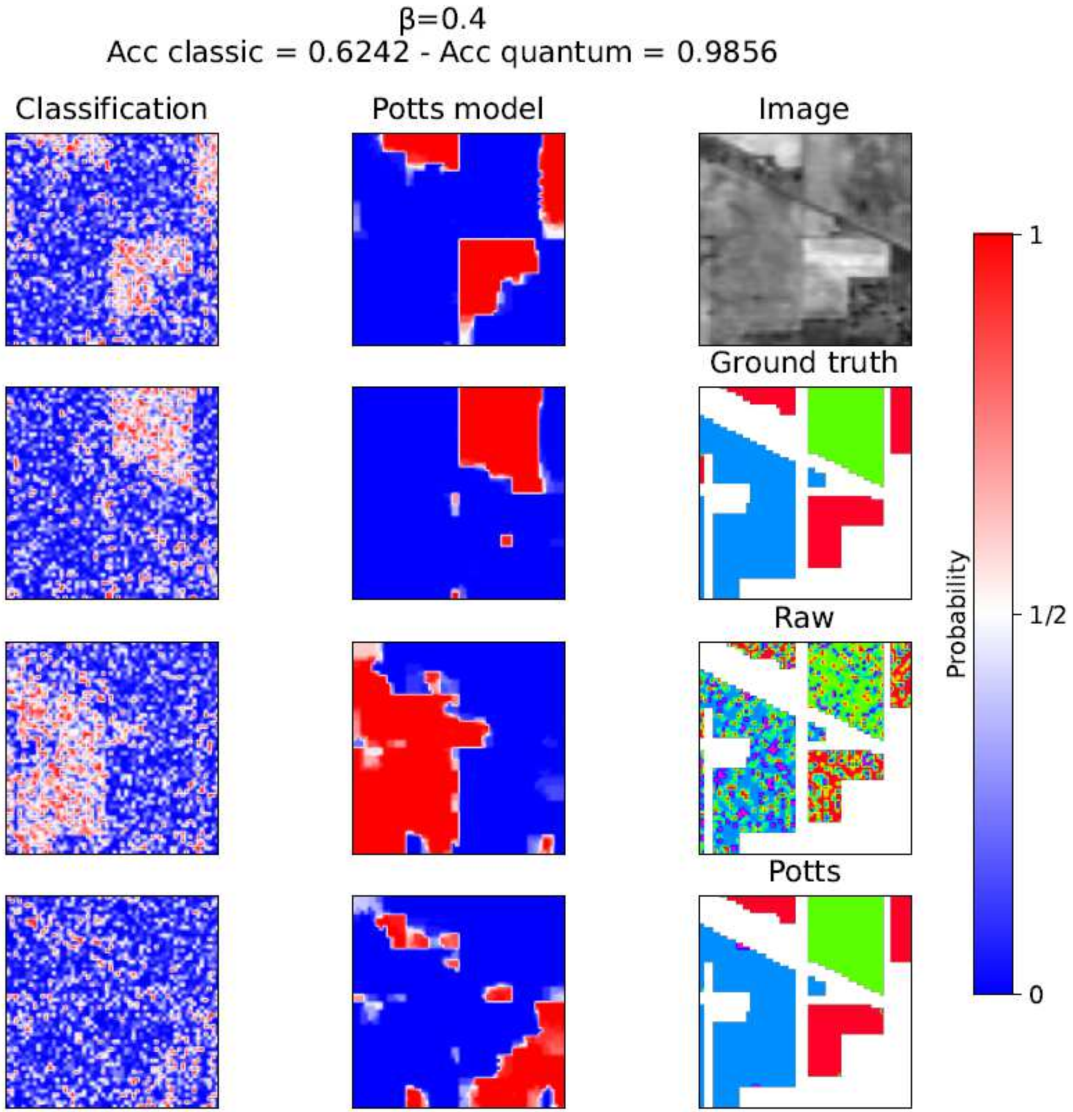
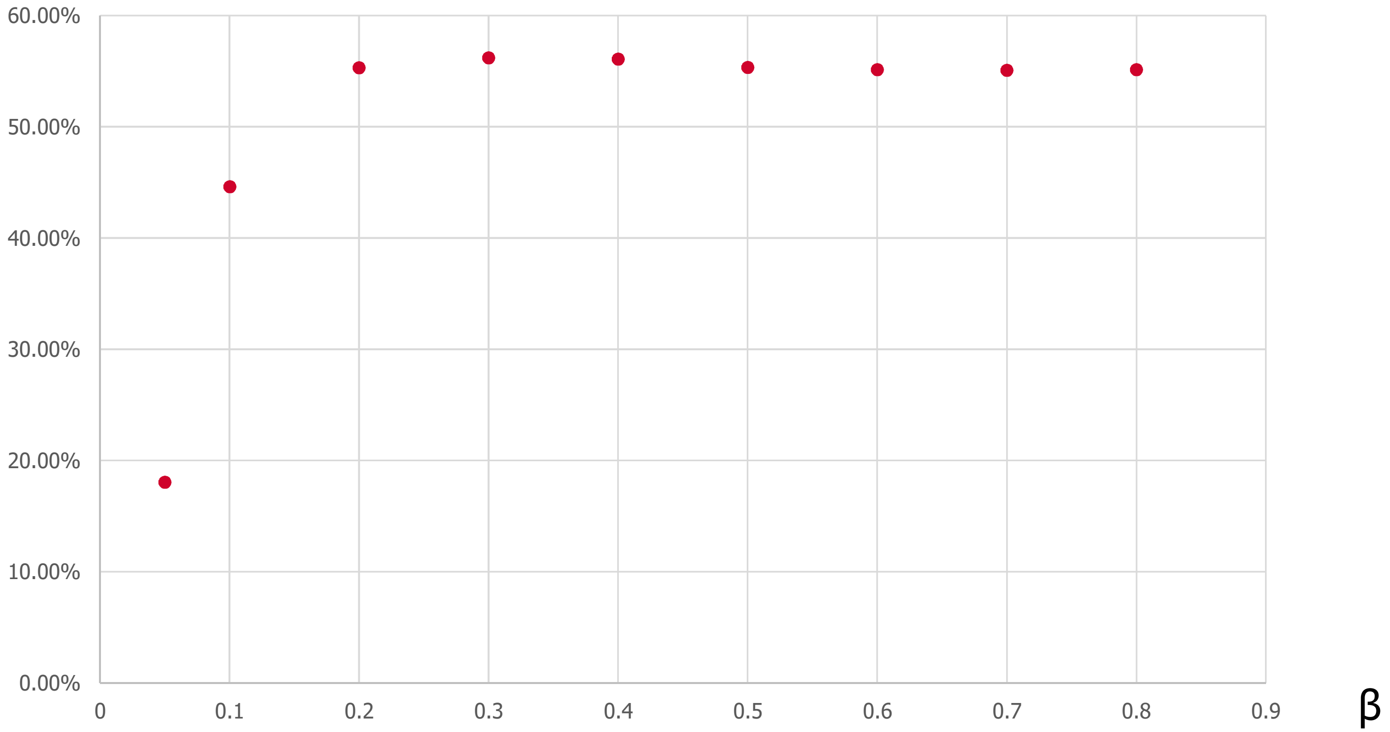
Ground truth with simulated noise

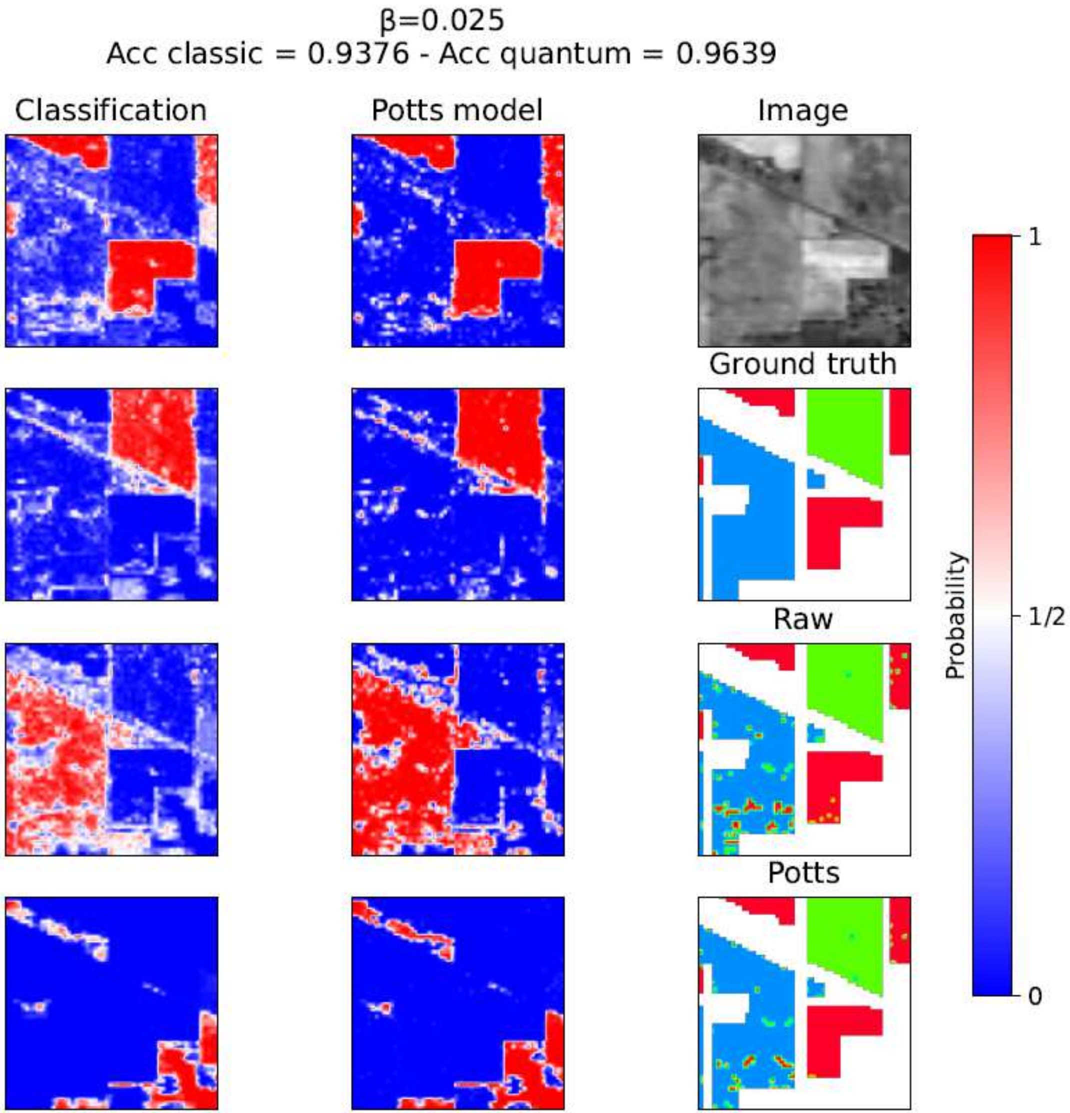


Quantum improvement

Ground truth with simulated noise



Pre-processing with Random Forest



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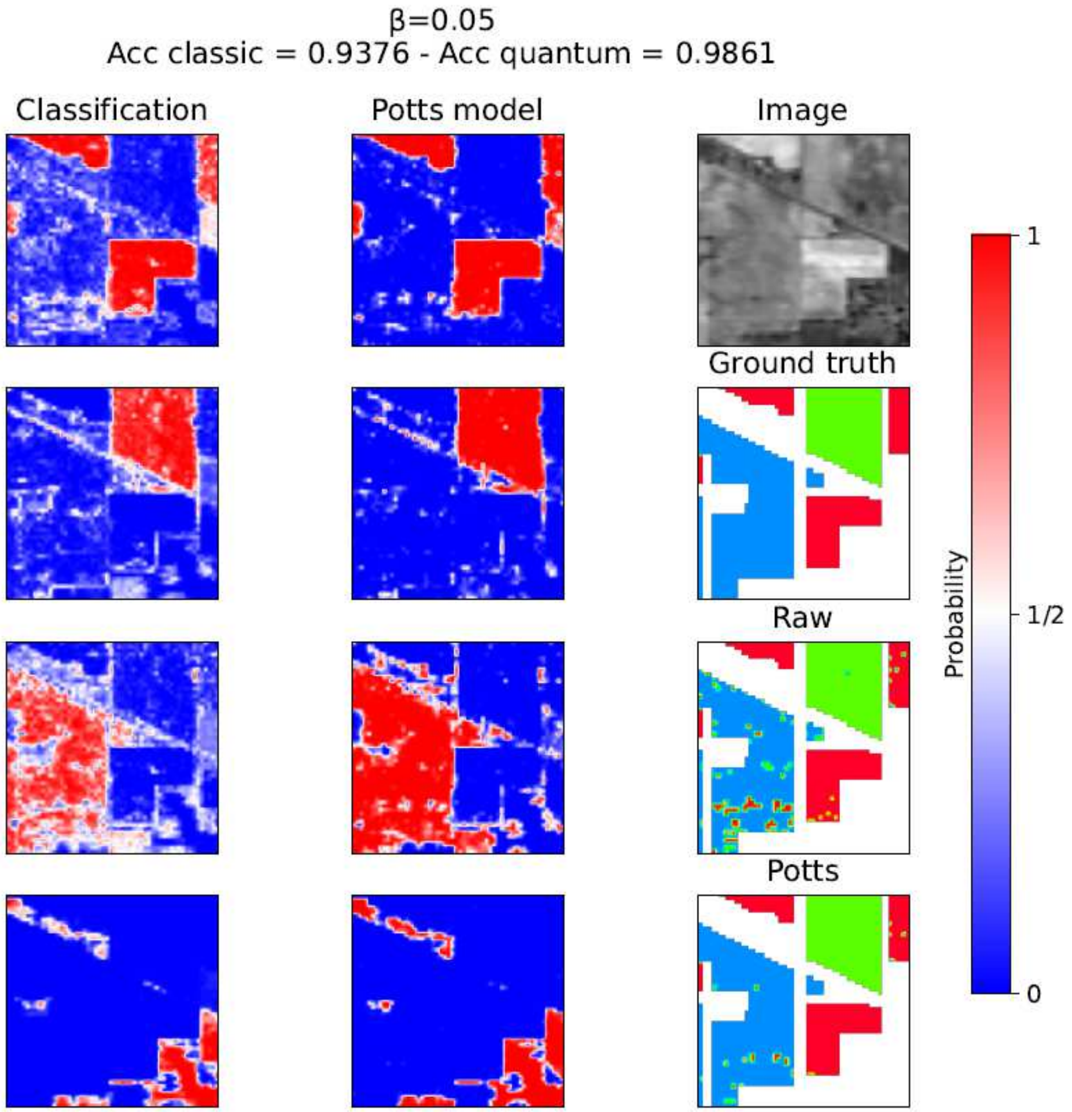
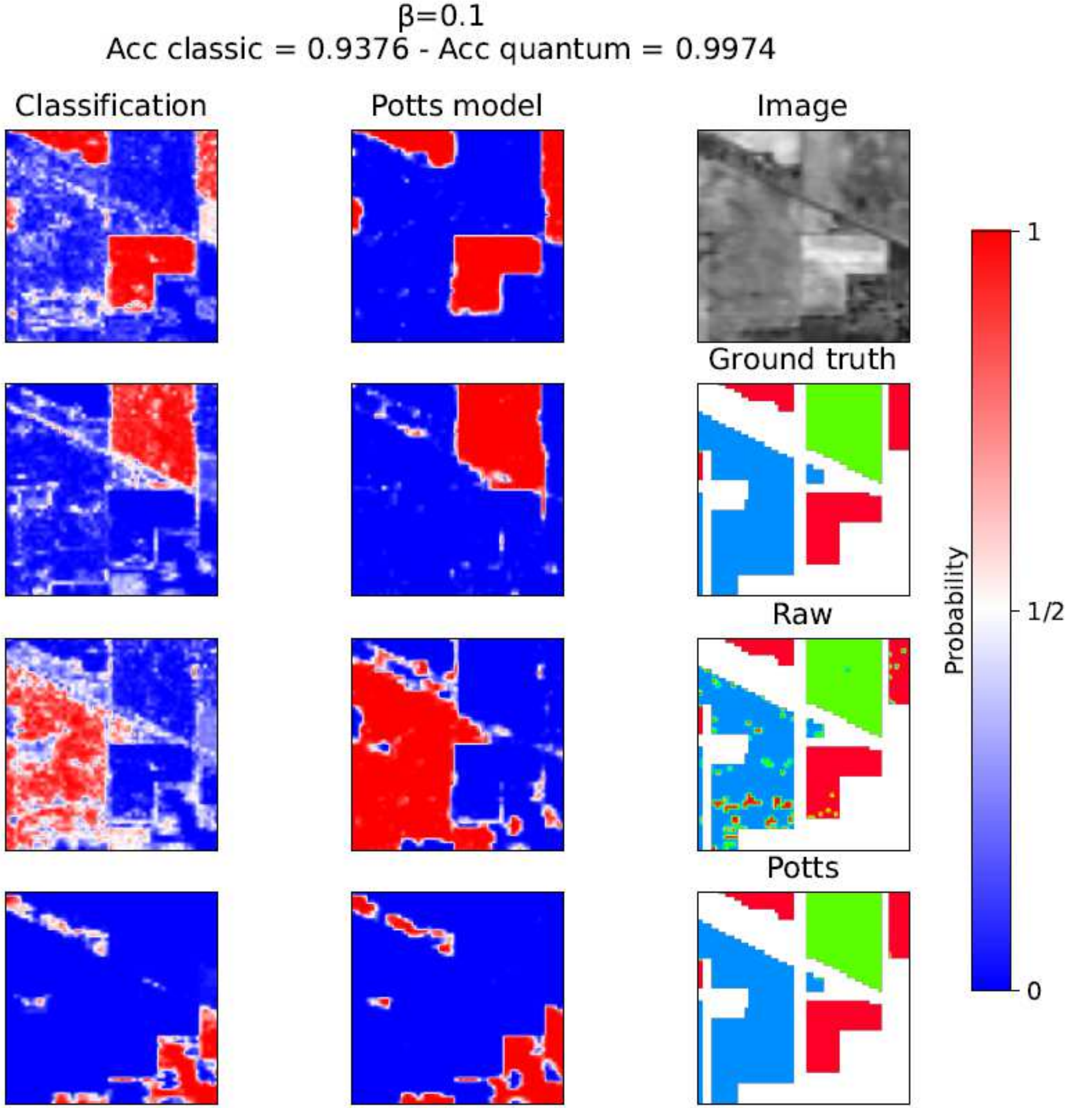
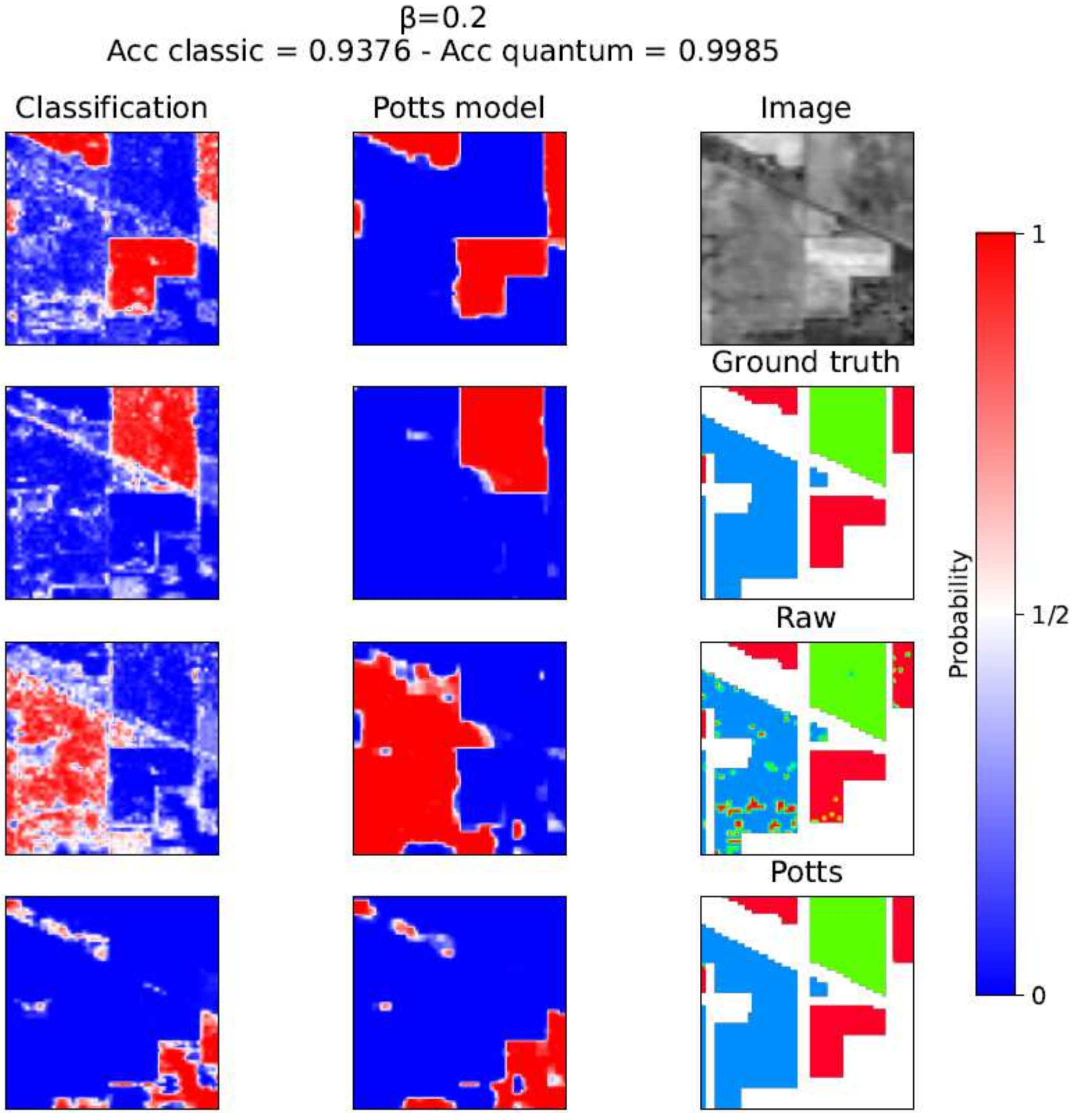
Pre-processing with Random Forest



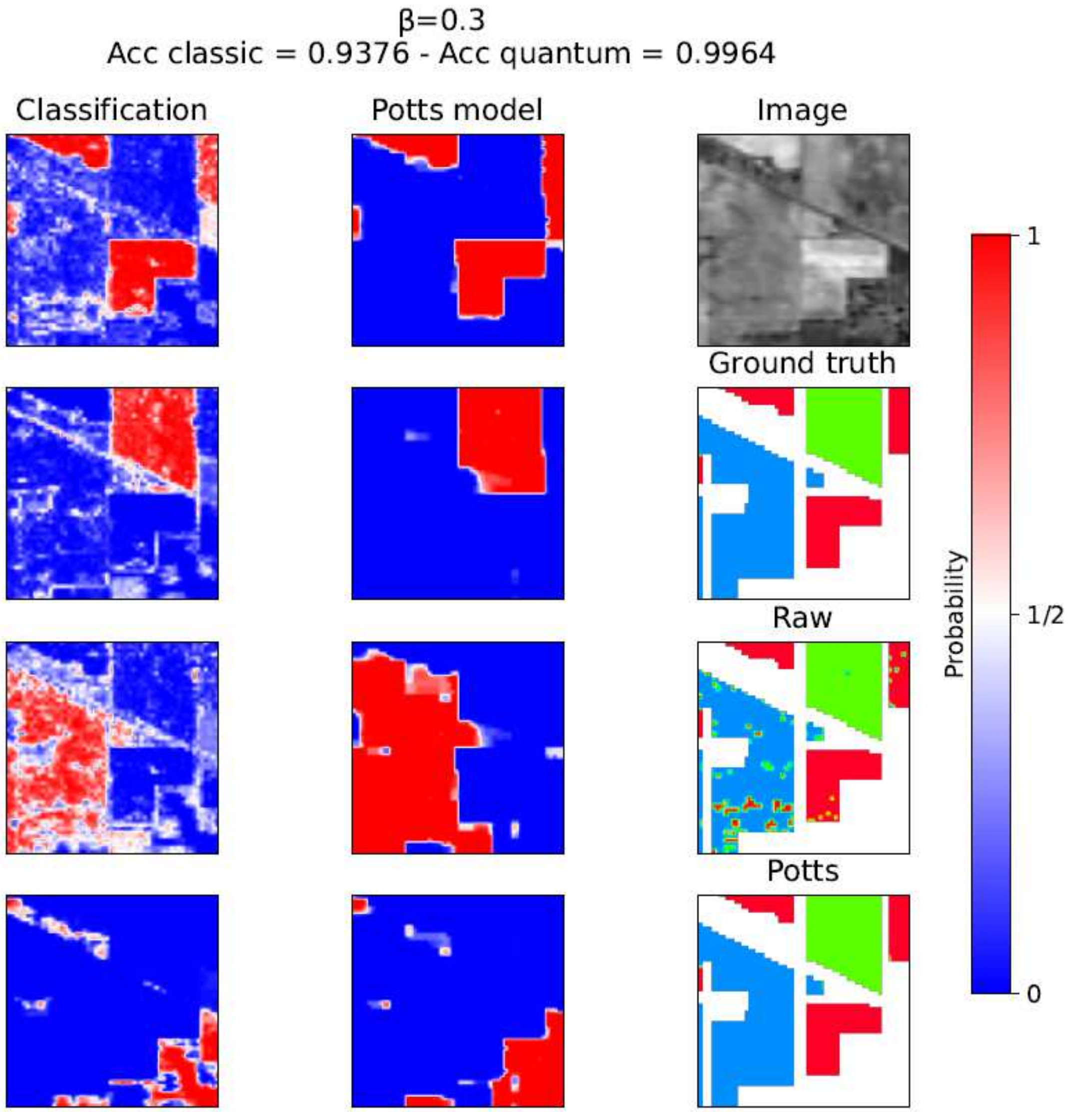
Pre-processing with Random Forest



Pre-processing with Random Forest

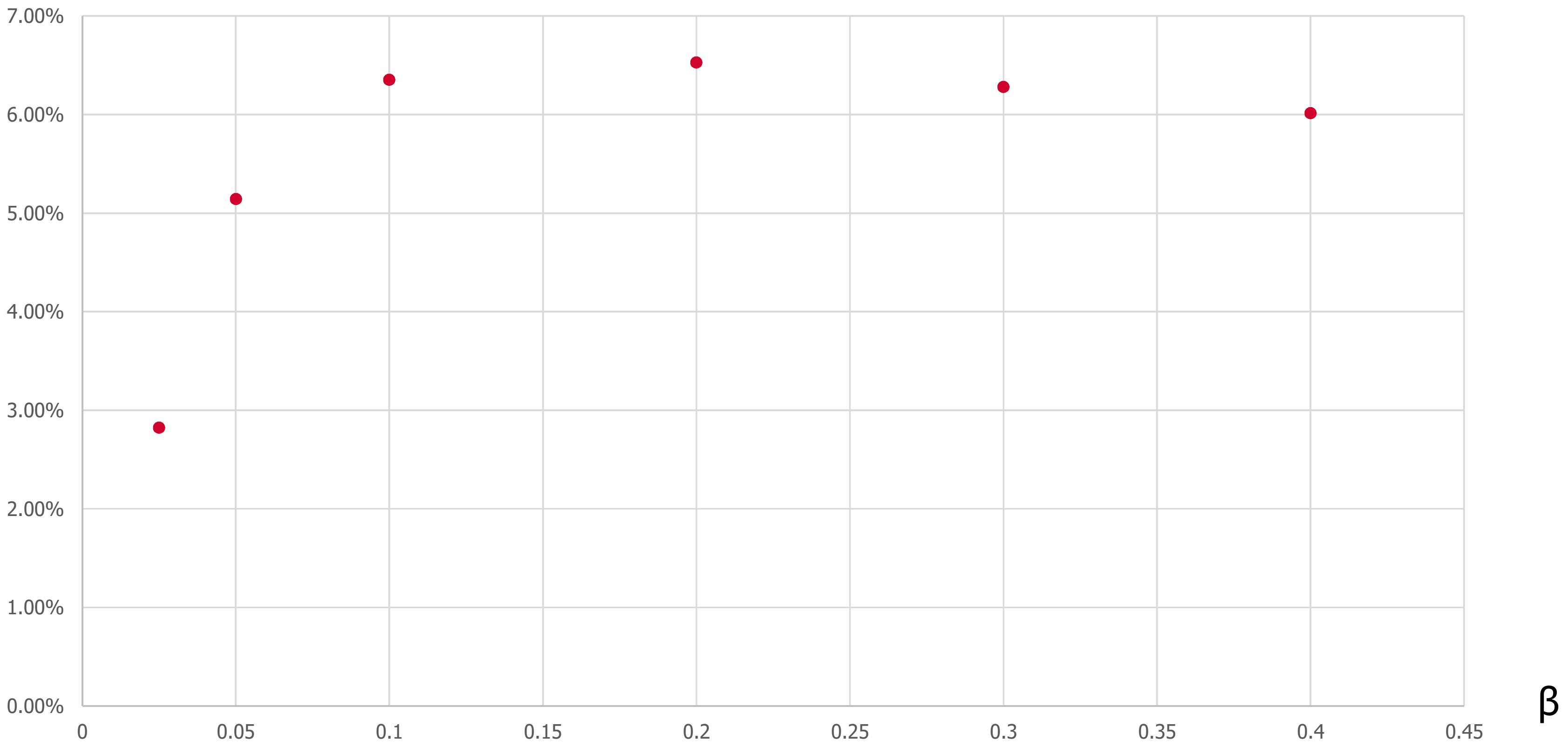


Pre-processing with Random Forest



Quantum Improvement

Pre-processing with Random Forest



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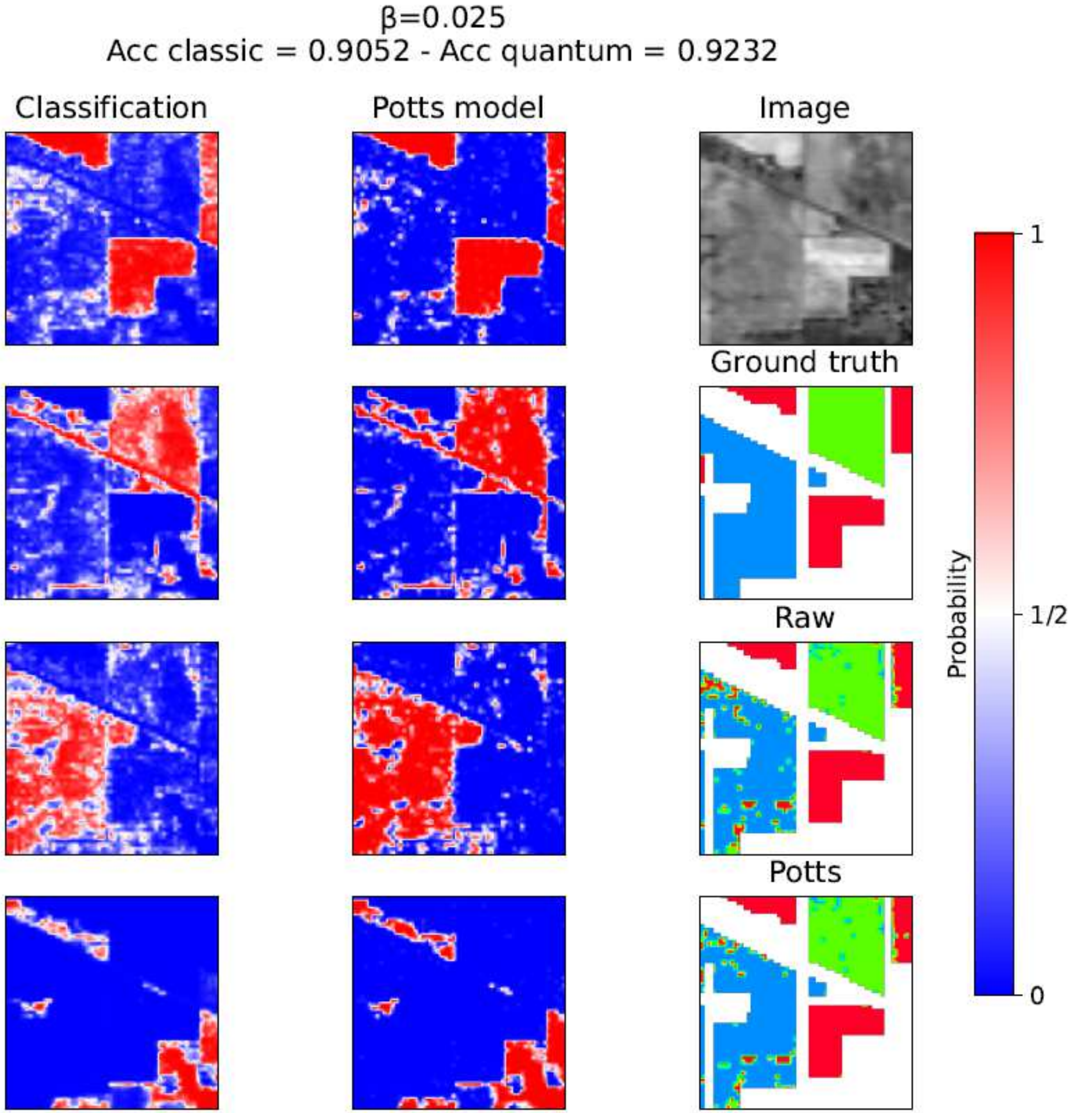
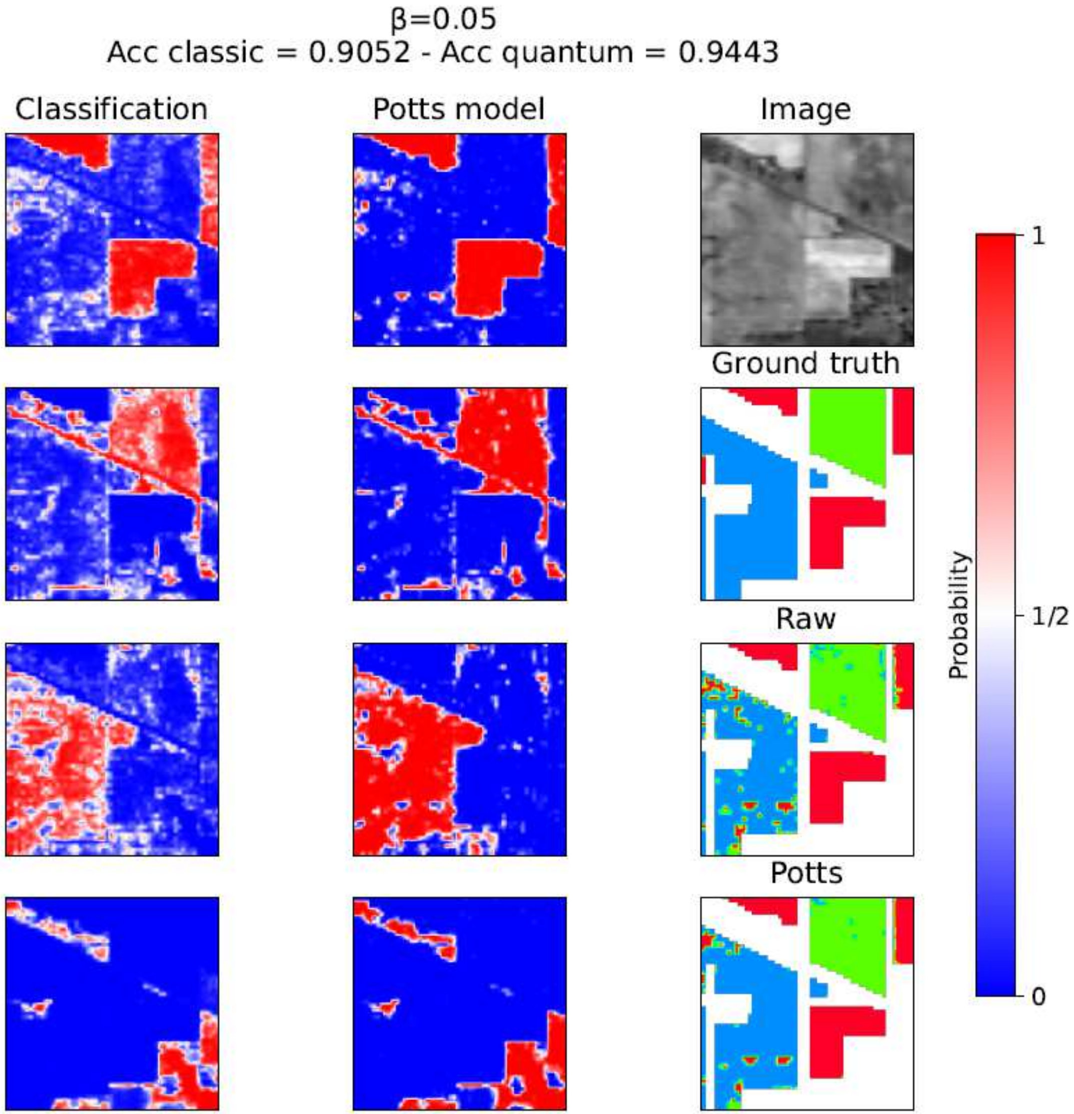
SVM

pre-processor



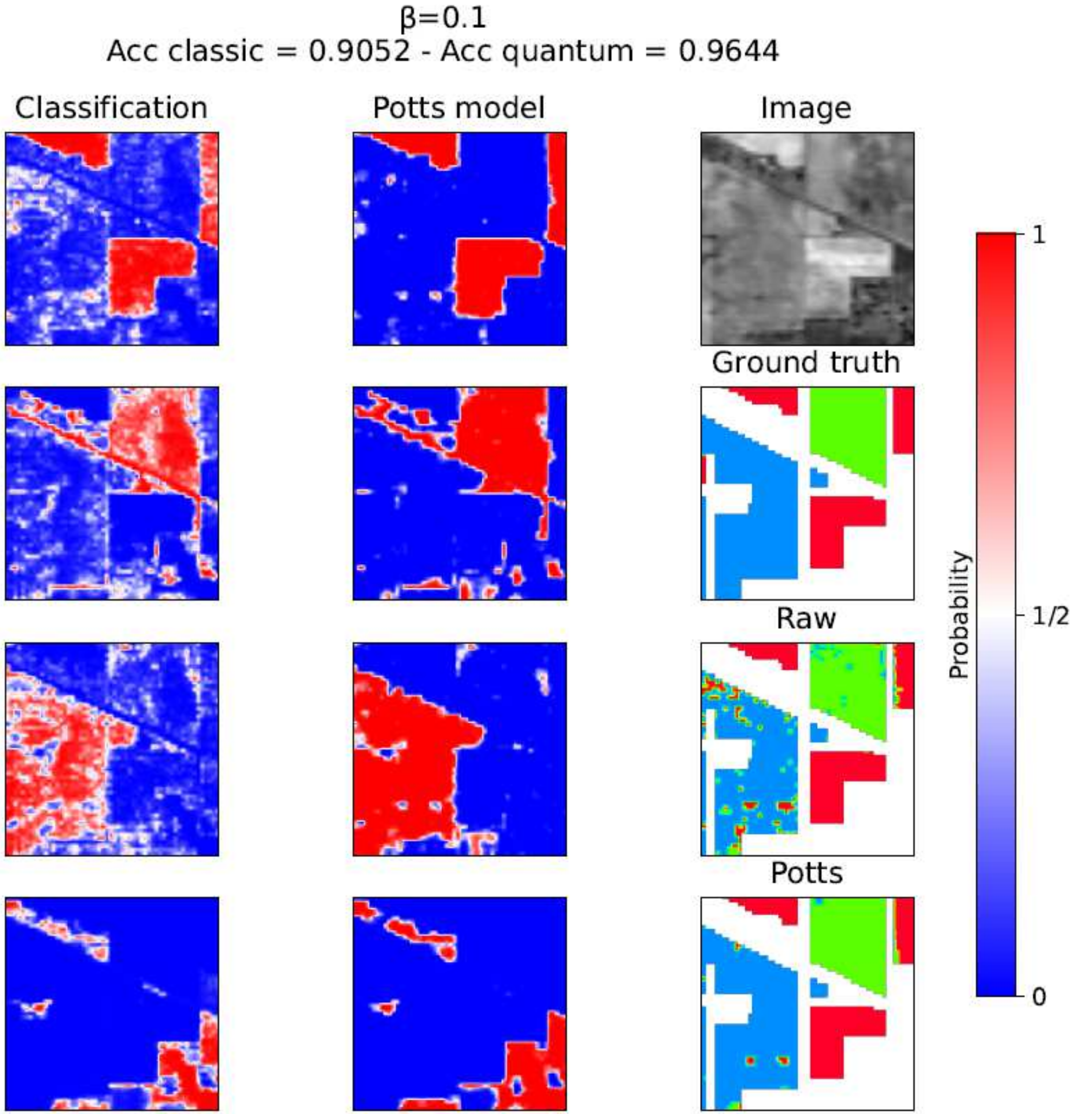


SVM

pre-processor

SVM

pre-processor



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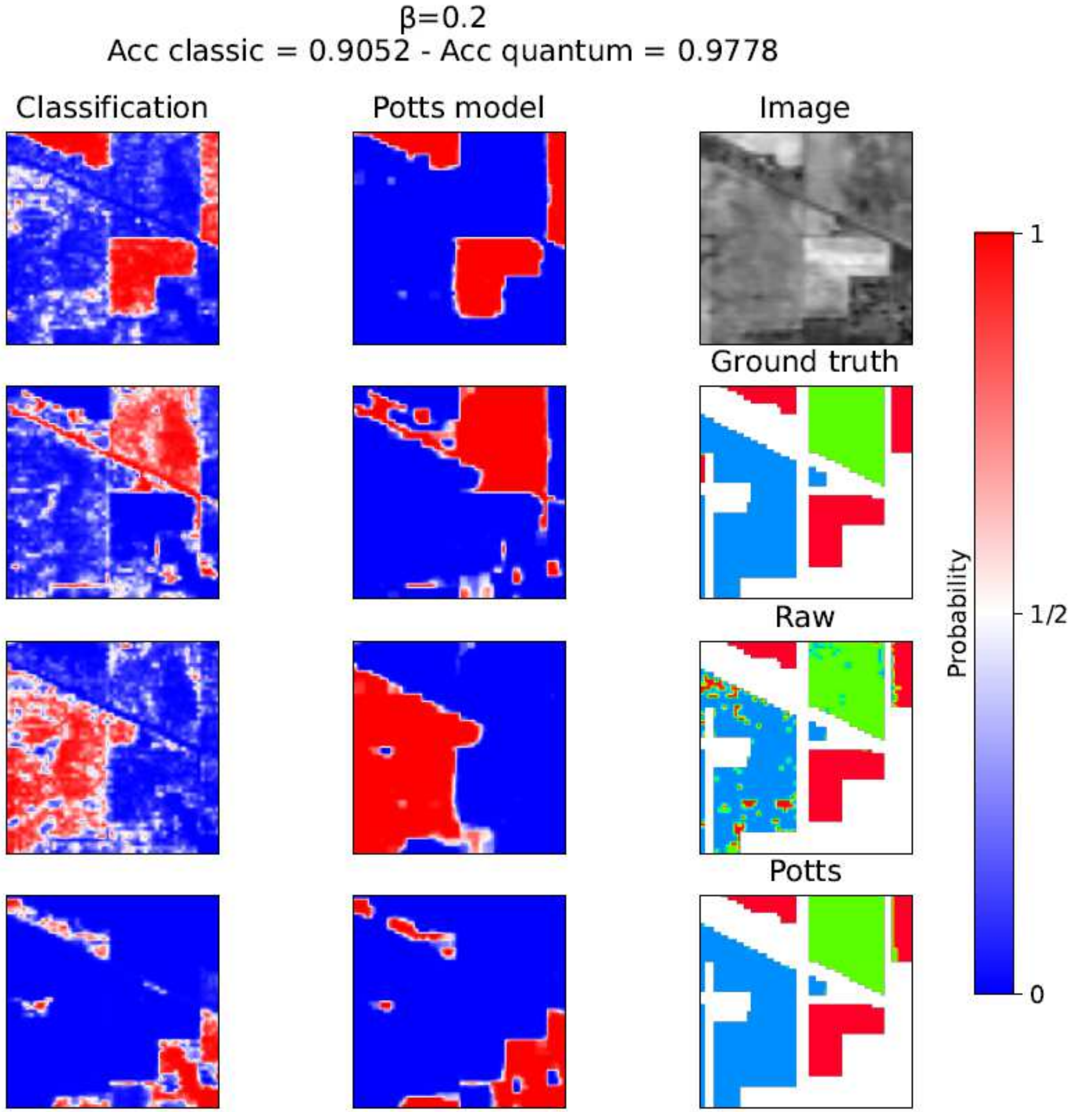
SVM

pre-processor



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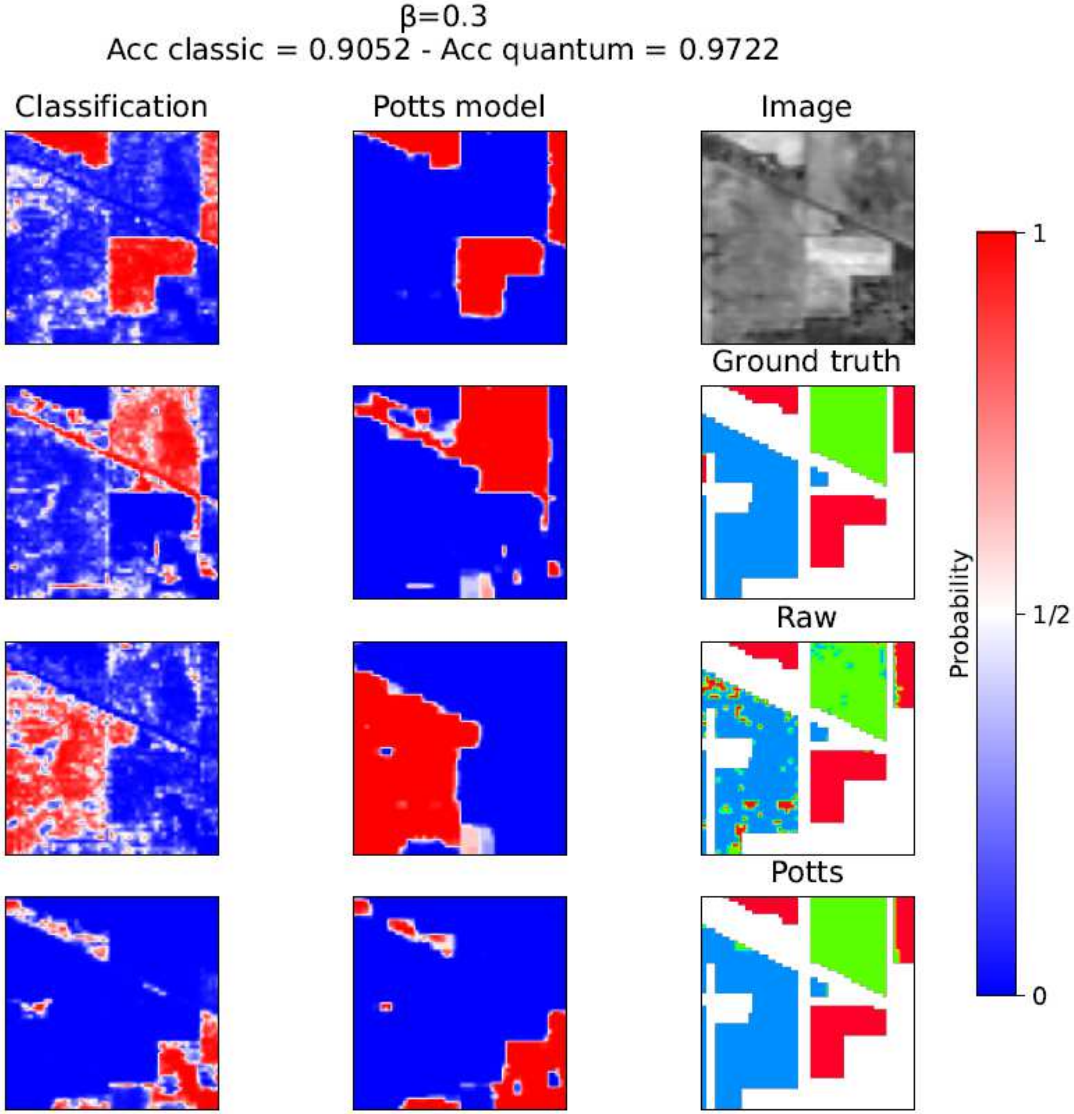
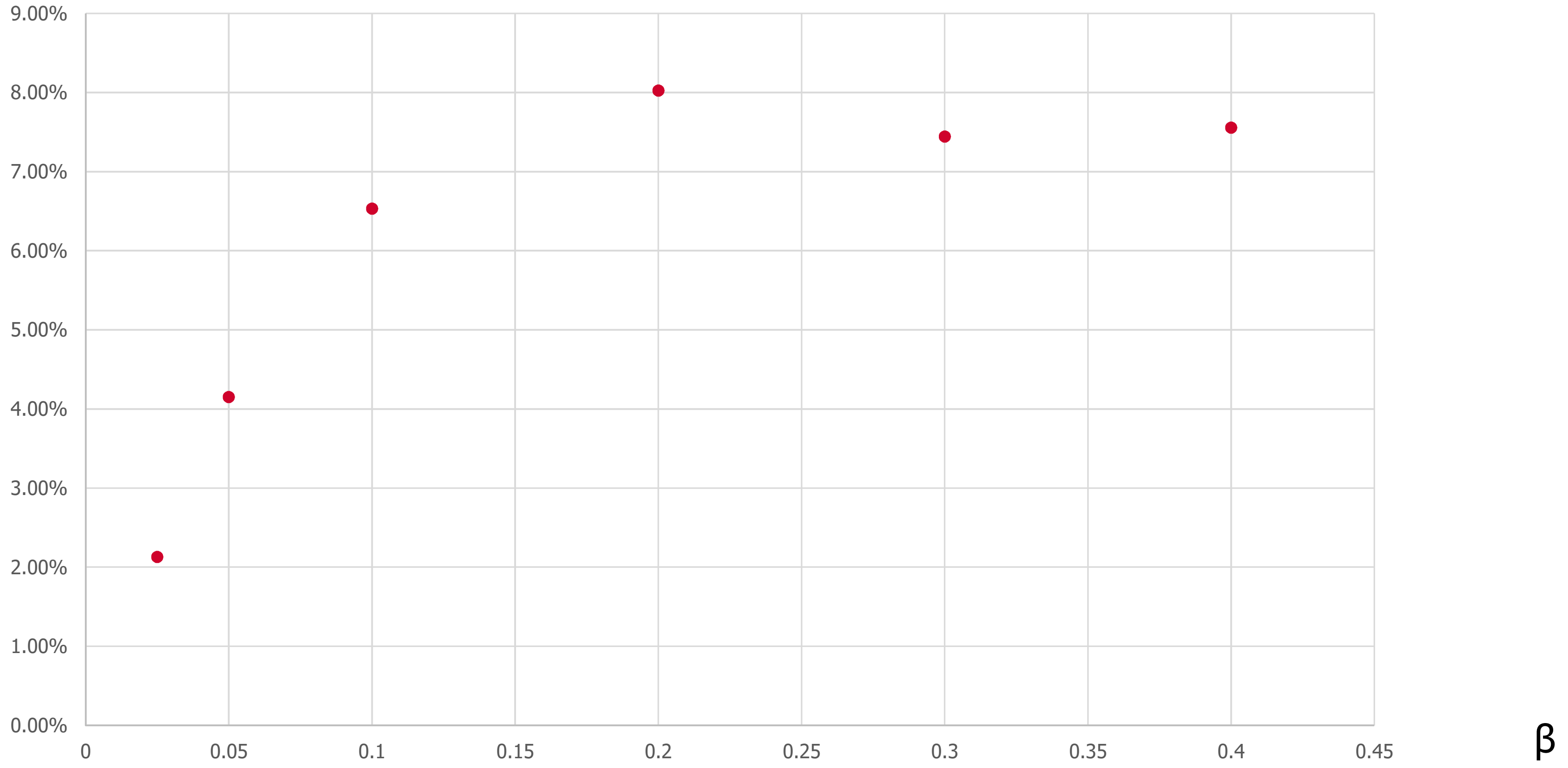
SVM

pre-processor



Quantum Improvement

Pre-processing with SVM



Conclusion

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Current state of the art

- We see improvements in the classification and segmentation accuracies
- Quantum speedup is possible if the quantum computers become more powerful
- Reduced energy usage will come with quantum speedup
- Quantum annealers claim to be production-ready
- Gate-based quantum computers are not yet production-ready

Thank you for your interest!

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