



# Quantum Neural Networks and Applications to Agriculture

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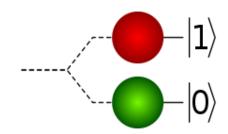
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#### Outline

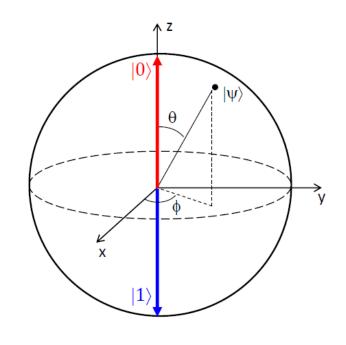
- Qubits
- Entanglement
- Quantum gates
- Quantum circuits
- Quantum neural networks
- Hybrid quantum neural networks
- Our research

#### Qubits

- Two state quantum mechanical system
  - basic unit of quantum information
  - quantum version of the classic binary bit
  - physically realized with a two-state device
- Examples:
  - spin of electrons up/down
  - polarization of photons left/right
- Coherent superposition of multiple states simultaneously
  - quantum mechanical property



#### Mathematical definition



Bloch sphere

Quantum binary digit (qubit)

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

• State  $|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$  with  $|\alpha|^2 + |\beta|^2 = 1$  can be represented by

Coherent superposition

– pure state

$$|\psi\rangle = \begin{bmatrix} \cos\frac{\theta}{2} \\ e^{i\phi} \sin\frac{\theta}{2} \end{bmatrix}$$

for  $\theta$  in  $[0, \pi]$  and  $\phi$  in  $[0, 2\pi]$ 

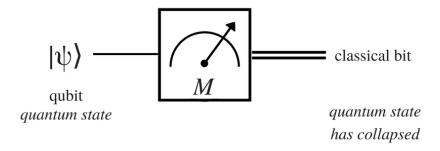
Standard basis is z-basis (North/South axis)

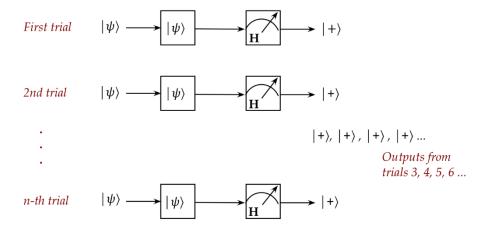
$$|0\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad |1\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Born rule – probability amplitudes

Vectors in a Hilbert space over complex field

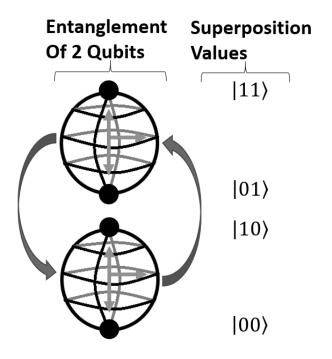
#### Measurements on Qubit

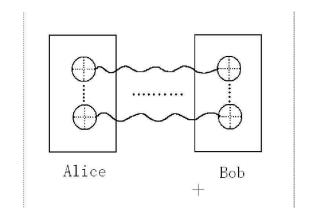




Expectations as probability amplitudes

#### Multiple Qubits: Entanglement





Bell state 
$$\left|\Psi\right\rangle = \frac{1}{\sqrt{2}}\left(\left|00\right\rangle + \left|11\right\rangle\right)$$

#### Multiple Qubits: Entanglement

An n-qubit system can exist in any superposition of the 2<sup>n</sup> basis states

$$c_0|00...00\rangle + c_1|00...01\rangle + \dots + c_{2^n-1}|11...11\rangle$$
, 
$$\sum_{i=0}^{2^n-1}|c_i|^2 = 1$$

If such a state can be represented as a tensor product of individual qubit states then the qubit states are **not entangled**. For example:

$$\left(\frac{1}{\sqrt{8}}|00\rangle + \frac{\sqrt{3}}{\sqrt{8}}|01\rangle + \frac{1}{\sqrt{8}}|10\rangle + \frac{\sqrt{3}}{\sqrt{8}}|11\rangle\right) = \left(\frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle\right) \otimes \left(\frac{1}{2}|0\rangle + \frac{\sqrt{3}}{2}|1\rangle\right)$$

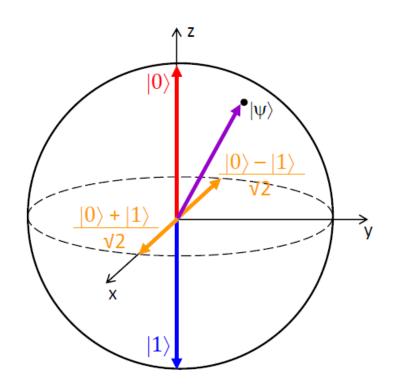
2<sup>n</sup> probability amplitudes

2n probability amplitudes

$$\left(\frac{1}{\sqrt{2}}|00\rangle + \frac{1}{\sqrt{2}}|11\rangle\right) \neq (a|0\rangle + b|1\rangle) \otimes (c|0\rangle + d|1\rangle)$$

#### Quantum Gates: Unitary Transformations

1-qubit logic gates: rotations around x, y and z axes



Pauli X - rotation by  $\pi$  around x axis

- implements NOT gate

Hadamard - rotation by  $\pi/2$  around y axis

and then by  $\pi$  around x axis

- creates equal superposition

when applied to |0
angle or |1
angle

We can define infinitely many logic gates operating on a single qubit

Any unitary 2x2 matrix (rotation) is a logic gate

#### NOT and Hadamard Gates

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$|1\rangle$$
  $X$   $|0\rangle$ 

Hadamard gate: creates superposition

$$\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \frac{1}{\sqrt{2}} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$
$$\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \frac{1}{\sqrt{2}} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$|0\rangle$$
  $H$   $\frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle$ 

$$|1\rangle$$
  $H$   $\frac{1}{\sqrt{2}}|0\rangle - \frac{1}{\sqrt{2}}|1\rangle$ 

### Controlled NOT (CNOT) – 2qubit gate

Truth table for the CNOT gate

Α	В	X	Υ
0	0	0	0
0	1	0	1
1	0	1	1
1	1	1	0

Quantum CNOT gate

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$



#### Quantum Logic Gates

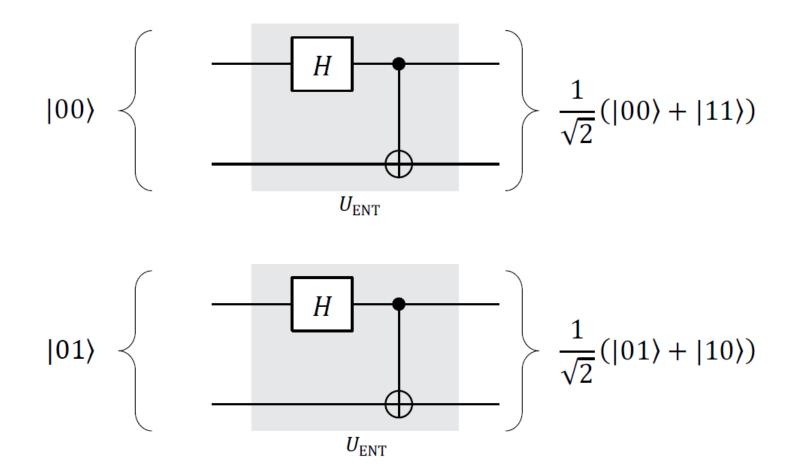
Rotation RY (Parameterised) Gates

$$R_y\left( heta
ight) = egin{pmatrix} \cos\left(rac{ heta}{2}
ight) & -\sin\left(rac{ heta}{2}
ight) \ \sin\left(rac{ heta}{2}
ight) & \cos\left(rac{ heta}{2}
ight) \end{pmatrix}$$

CNOT and SWAP are universal 2-qubit gates

Operator	Gate(s)		Matrix
Pauli-X (X)	$-\mathbf{x}$		$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$
Pauli-Y (Y)	$- \boxed{\mathbf{Y}} -$		$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}$
Pauli-Z (Z)	$- \boxed{\mathbf{z}} -$		$\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$
Hadamard (H)	$-\mathbf{H}$	$rac{1}{\sqrt{2}}egin{bmatrix}1&&1\1&&-1\end{bmatrix}$	
Phase (S, P)	$- \boxed{\mathbf{S}} -$		$\begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}$
$\pi/8~(\mathrm{T})$	$-\!$		$\begin{bmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{bmatrix}$
Controlled Not (CNOT, CX)	<u> </u>		$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$
Controlled Z (CZ)		<b>†</b> [	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$
SWAP		<del>_</del>	$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$
Toffoli (CCNOT, CCX, TOFF)		$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \end{bmatrix}$	$ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 &$

#### Creation of Entangled States with Gates



#### Wiring the Gates

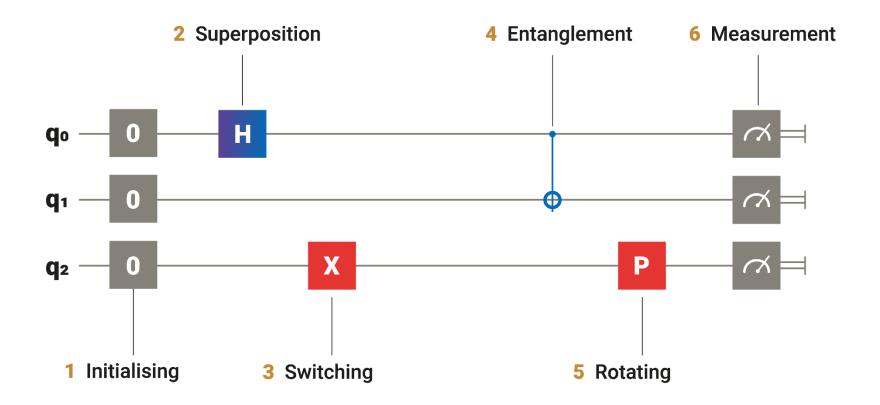
$$|\psi\rangle$$
  $Y$   $X$   $XY$   $|\psi\rangle$ 

Serial wiring

$$|\psi\rangle - Y - Y |\psi\rangle \qquad \Leftrightarrow \qquad |\psi\rangle - Y \otimes X - \begin{cases} (Y \otimes X) |\psi \otimes \phi\rangle \\ |\phi\rangle - X - X |\phi\rangle \end{cases}$$

Parallel wiring

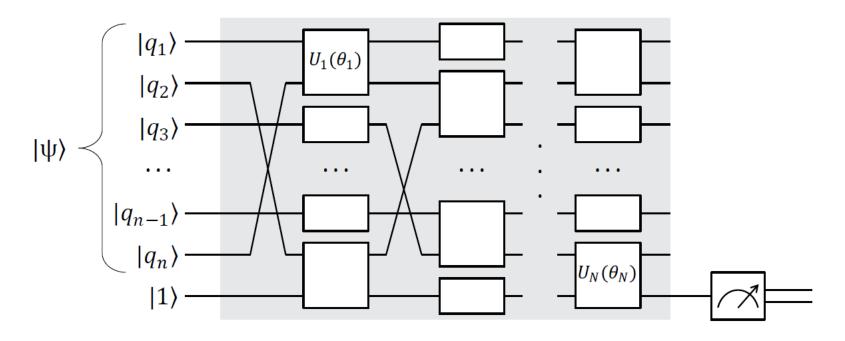
#### Quantum Circuits



#### Quantum Circuit Rules

- Not all quantum circuits are valid
- Gates are applied sequentially left to right state evolution
- Wires represent identity matrices ("do nothing")
- There are no loops
- Number of qubits is preserved

#### Parameterised Quantum Circuits

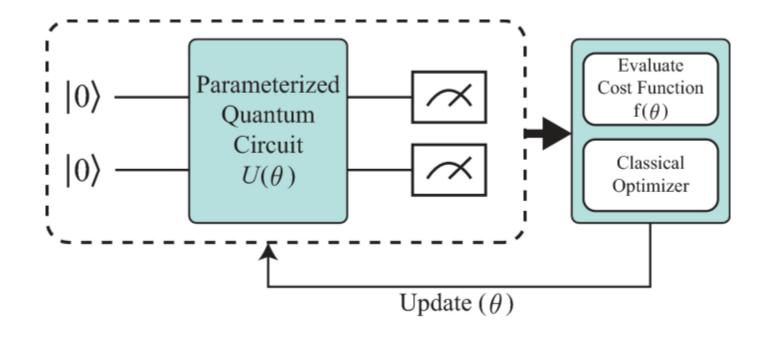


$$|\psi\rangle = |q_1, q_2, ..., q_n\rangle$$
 Input qubit vector

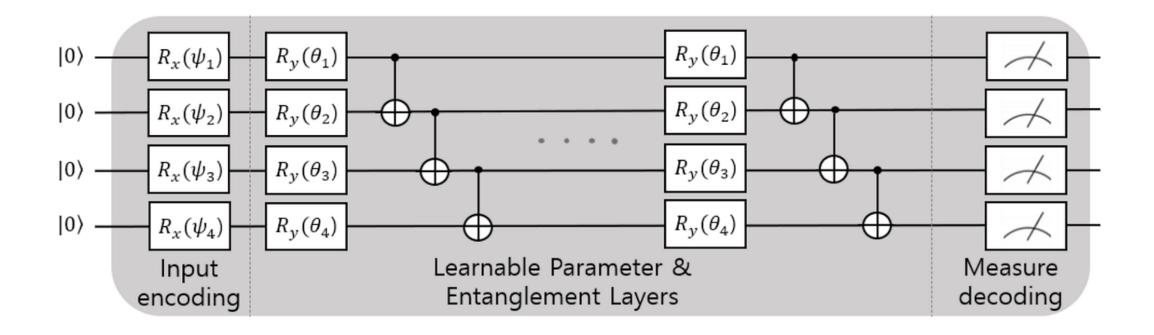
 $U(\theta)$  1 and 2 bit Unitaries

Parameters  $\theta$  are adjusted during learning such that the measurement on the readout qubit tends to produce the desired label for  $|\psi\rangle$ .

#### Variational Quantum Circuits



#### Quantum Neural Networks



#### How to train your QNN?

#### Two approaches:

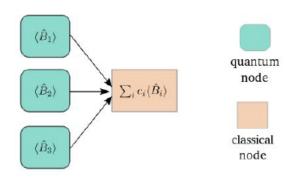
- Simulator-based
  - Build simulation **inside existing classical library**
  - Can leverage existing optimization & ML tools
  - Great for small circuits, but **not scalable**





#### II. Hardware-based

- No access to quantum information; only have measurements & expectation values
- Needs to work as hardware becomes more powerful and cannot be simulated



#### Gradient of Quantum Circuits

- Training strategy: use gradient descent algorithms.
- Need to compute gradients of variational circuit outputs w.r.t. their free parameters.

 How can we compute gradients of quantum circuits when even simulating their output is classically intractable?

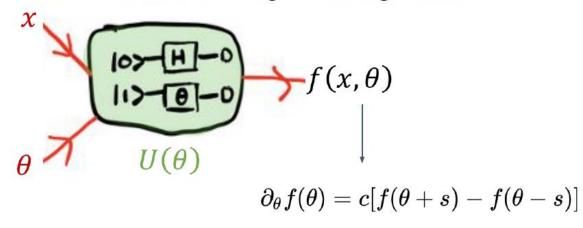
#### Computing the Gradient

- No cloning of information between the layers
  - Unlike classical neural networks
- Fan-out unitary gate
- Ancilla bit

#### Parameter Shift Trick

#### Use the same device to compute a function and its gradient

"Parameter shift" differentiation rule: gives exact gradients



$$\Delta t = t(\Theta') - t(\Theta')$$



- o Minimal overhead to compute gradients vs. original circuit
- Optimize circuits using gradient descent
- Compatible with classical backpropagation: hybrid models are end-to-end differentiable

### Training Methods

Gradient-based Optimisation

Bayesian Optimisation

Particle Swarm Optimisation

Genetic Algorithm

Jin-Guo Liu and Lei Wang (2018)

Differentiable Learning of Quantum Circuit Born Machine

https://arxiv.org/abs/1804.04168

X. Gao, Z.-Y. Zhang and L.-M. Duan (2017)

An efficient quantum algorithm for generative machine learning

https://arxiv.org/abs/1711.02038

D. Zhu, N. M. Linke et al (2018)

Training of quantum circuits on a hybrid quantum computer

https://arxiv.org/abs/1812.08862

Marcello Benedetti, Delfina Garcia-Pintos et al (2019)

A generative modelling approach for benchmarking and training shallow quantum circuits

https://arxiv.org/abs/1801.07686

Alexei Kondratyev and George Giorgidze (2017)

Evolutionary Algos for Optimising MVA, Risk, December 2017

https://www.risk.net/cutting-edge/banking/5374321/evolutionary-algos-for-

optimising-mva

Davide Venturelli and Alexei Kondratyev (2019)

Beyond Markowitz with Quantum Annealing, Risk, June 2019

https://www.risk.net/asset-management/6685986/beyond-markowitz-with-

quantum-annealing

Alexei Kondratyev (2020)

Non-Differentiable Learning of Quantum Circuit Born Machine with Genetic

Algorithm

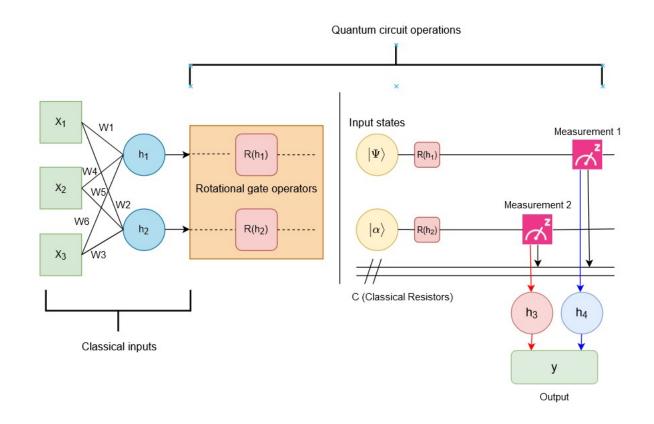
https://ssrn.com/abstract=3569226

#### **QNN Summary**

- Decision choices
  - Input encoding quantum embedding
  - Parameterised circuit topology
  - Cost function

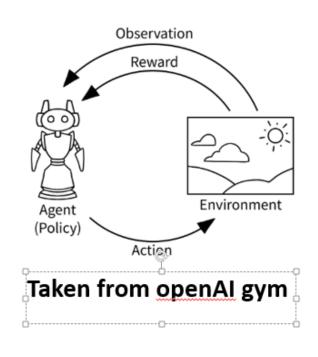
- Advantages
  - More expressive power with less number of nodes
  - Parallel computation

#### Hybrid Quantum Neural Networks



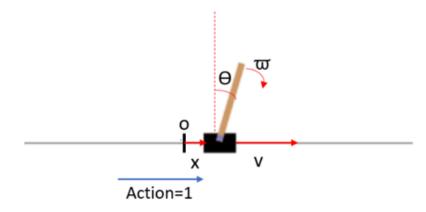
M. Das, A. Naskar, P. Mitra, B. Basu (2024) Shallow quantum neural networks (SQNNs) with application to crack identification, Applied Intelligence

#### QNN for Optimal Control



Investigation of the performance and behavioural differences that Hybrid Quantum-Classical Reinforcement Learning agents have in comparison to Classical RL agents, specifically with respect to the sample efficiency and result stability of the relevant models

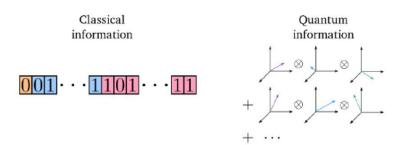
#### **CartPole Stabilization problem**



E. Mitchell, B. Basu, P. Mitra (2024) Performance analysis of a quantum-classical hybrid reinforcement learning, ICLR 2024, Vienna.

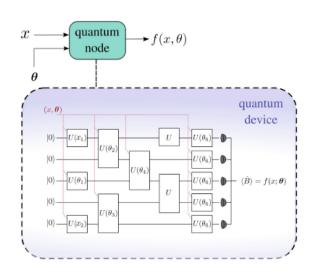
### Quantum Node – A Programming Construct

Classical and quantum information are distinct

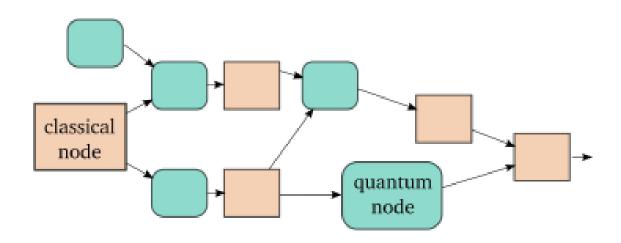


# QNode: common interface for quantum and classical devices

- Classical device sees a callable parameterized function
- Quantum device sees fine-grained circuit details



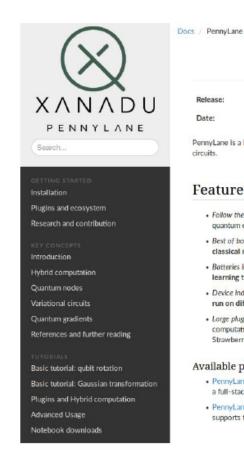
## Hybrid Networks – Differentiable Computing



# PennyLane

#### "The TensorFlow of quantum computing"

- Train a quantum computer the same way as a neural network
- Designed to scale as quantum computers grow in power
- Compatible with Xanadu, IBM, Rigetti, and Microsoft platforms



PENNYLANE

/ Show Source / O Show on GitHub

devl - qnl.device|'default.qubit', wires-

cost = qml.grad(cost, argnum=[0, 1])

Release: 0.1.0 Date: 2018-11-07

PennyLane is a Python library for building and training machine learning models which include quantum computer

#### Features

- . Follow the gradient. Built-in automatic differentiation of quantum circuits
- . Best of both worlds. Support for hybrid quantum and classical models
- · Batteries included. Provides optimization and machine
- · Device independent. The same quantum circuit model can be run on different backends
- · Large plugin ecosystem. Install plugins to run your computational circuits on more devices, including Strawberry Fields and ProjectQ

#### Available plugins

- . PennyLane-SF; Supports integration with Strawberry Fields. a full-stack Python library for simulating continuous variable (CV) quantum optical circuits.
- PennyLane-PQ: Supports integration with ProjectQ, an open-source quantum computation framework that supports the IBM quantum experience.

https://github.com/XanaduAl/pennylane

https://pennylane.ai



#### Other ecosystem

PENNYLANE O'PyTorch TensorFlow



STRAWBERRY FIELDS

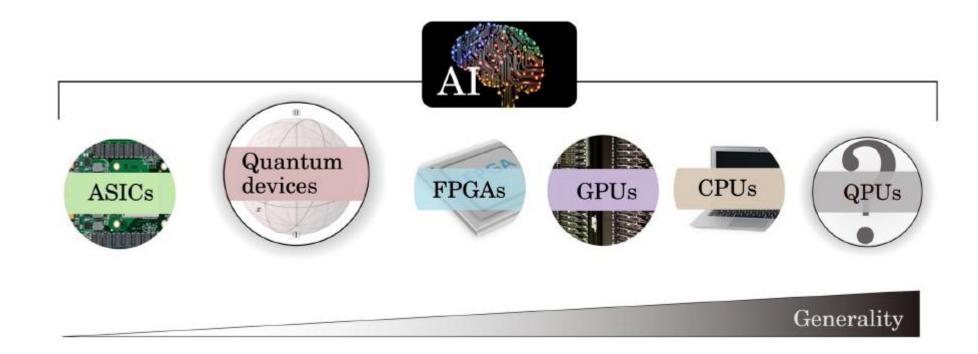






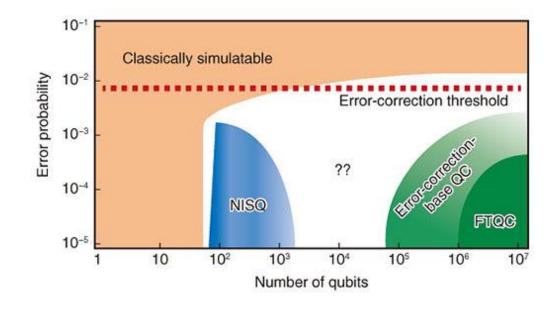


#### Quantum Processing Units

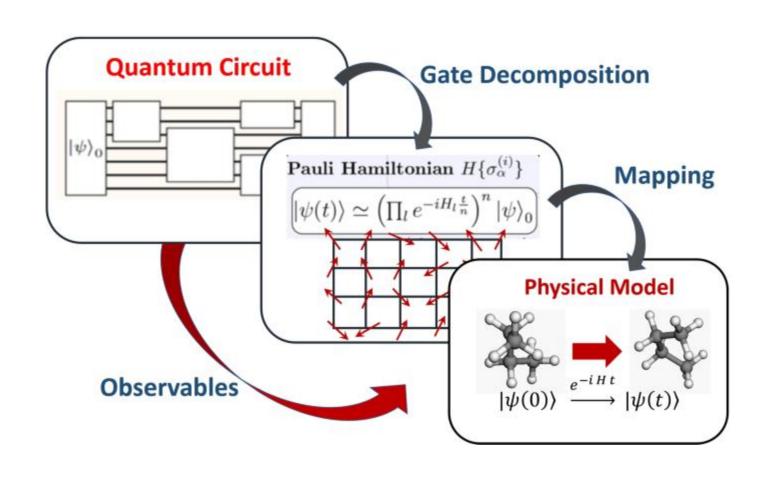


#### Noisy Intermediate Scale Quantum Era (NISQ)

- Upto 1000 qubits
- Suffers from decoherence
  - No error correction
- No fault tolerance



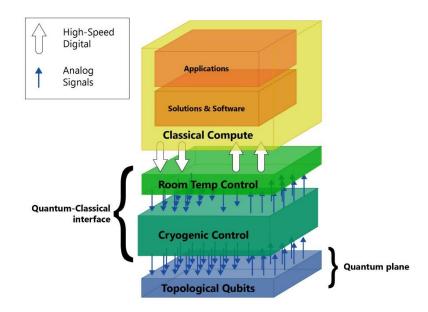
#### NISQ Processor Design



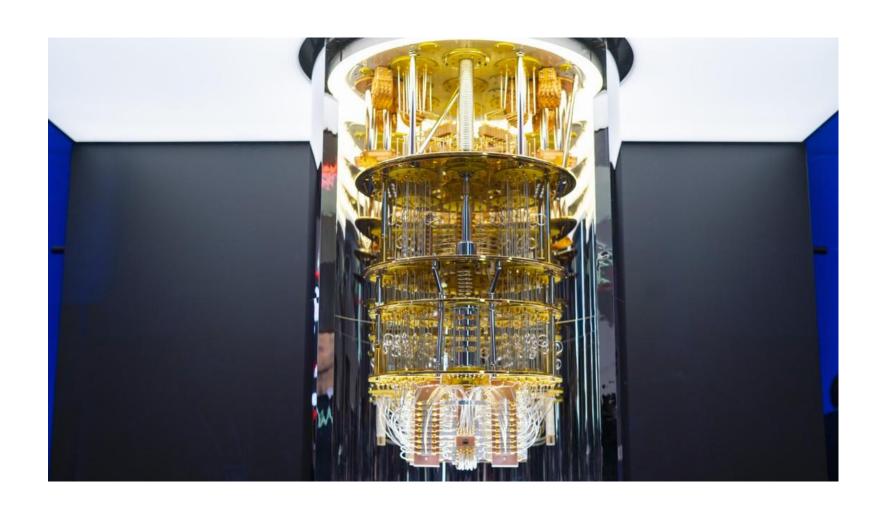
#### Quantum Processors

- Circuit based
- Annealing based
- Analog
- IBM
- Google
- Intel
- Riggeti
- Xanadu

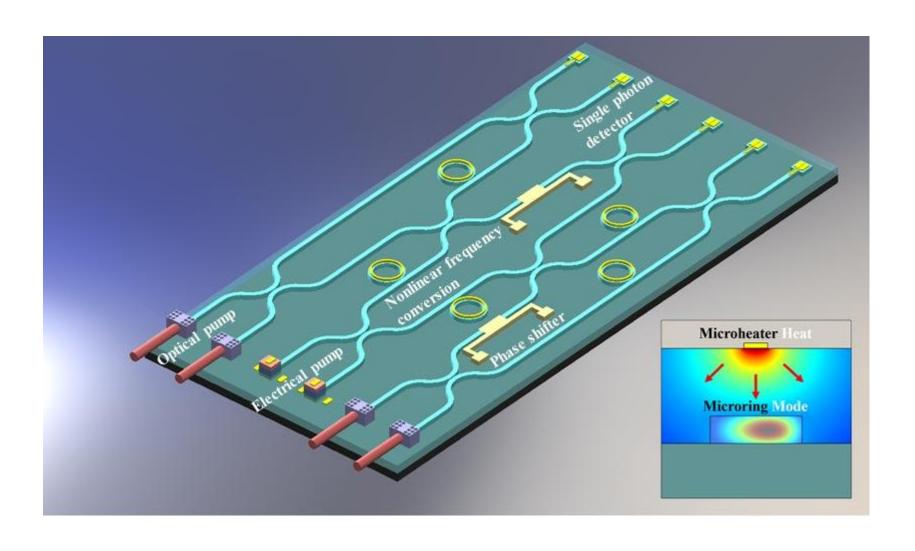
- Superconducting
- Photonics
- Semiconductor spin
- Trapped ion



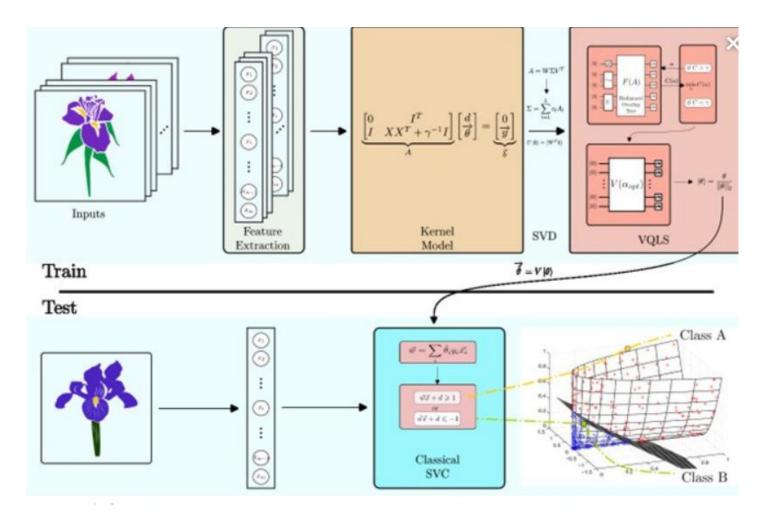
# IBM Superconducting Quantum Processor



#### Photonic Quantum Processor



## QNN for Plant Image Feature Extraction



EQID: Entangled quantum image descriptor an approach for early plant disease detection, Attri et al, Crop Protection, 2025

#### QNN for Plant Image Enhancement

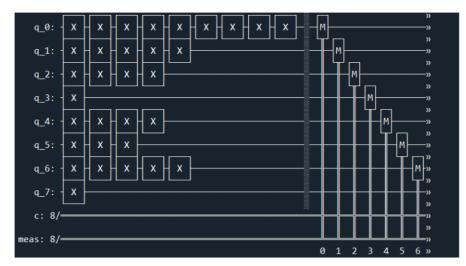
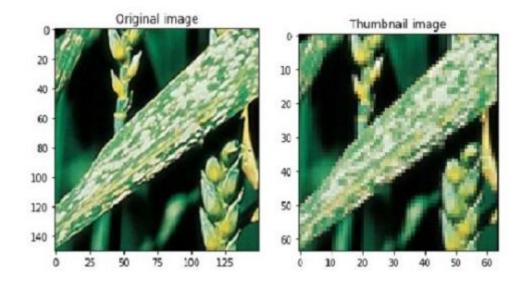
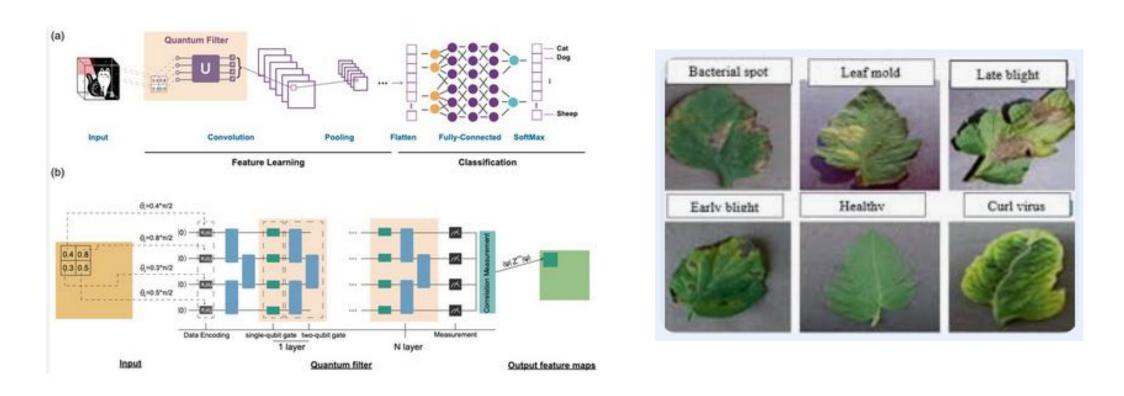


Fig. 6. Quantum contrast enhancement and noise filtering circuit.



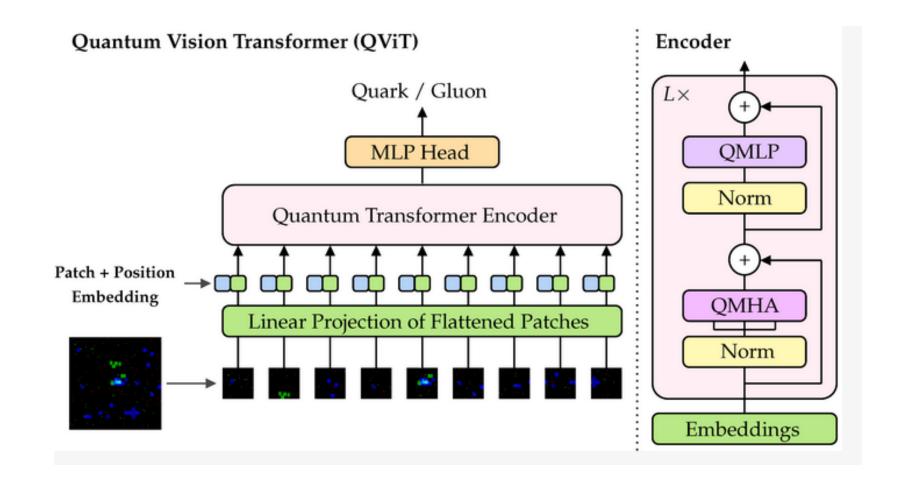
Application of quantum computing in image processing for recognition of infectious diseases of wheat, Mukhadieveda et al (CIBTA-III-2024)

#### Quantum Convolutional Neural Network



Quantum Convolutional Neural Network for Agricultural Mechanization and Plant Disease Detection, (ICIPCN 2023)

#### Quantum Vision Transformers



#### National Quantum Mission



To build a 1000 qubit quantum computer

- Computing
- Communication
- Sensing
- Material science

Thank you!