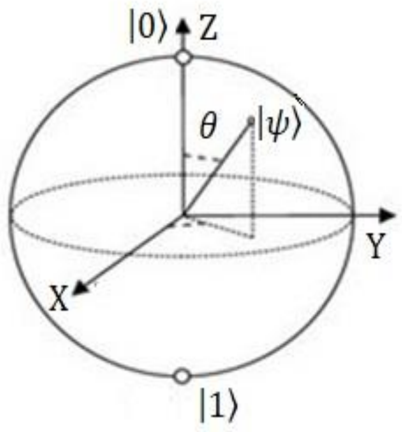
Quantum computers and their hybrid implementations

Ravi Kumar Jha
Intelligent Systems Research Centre
Ulster University, Londonderry, U.K.
Email: Jha-R@ulster.ac.uk



N3BG Summer School 2025, TU Sofia

Vision

- *Quantum mechanics* – physics of particles at subatomic scales

- “There's Plenty of Room at the Bottom” (APS Meeting, 1959)

Richard Feynman

> “When we get to the very, very small world – say circuits of seven atoms – we have a lot of new things that would happen that *represent completely new opportunities for design*. Atoms on a small scale behave like nothing on a large scale, for they satisfy the laws of *quantum mechanics*…”

Quantum Mechanics

- *Quantum mechanics* is the theory that describes the behavior of microscopic systems, such as *photons, electrons, atoms, molecules*, and *others*

"Nobody understands quantum mechanics!" – Feynman

- *Quantum states or wavefunction*, $|\psi\rangle$, evolve over time according to the Schrödinger equation:

$$i\hbar \frac{\partial}{\partial t}|\psi\rangle = \hat{H}|\psi\rangle,$$ where H is the Hamiltonian

- This implies that *time evolution* is described by unitary transformations: $|\psi\rangle \longrightarrow \hat{H}|\psi\rangle$
- Quantum systems are *inherently nondeterministic* and *probabilistic in nature*, a fact that has been extensively confirmed through experiments

Quantum Theory & Technology Evolution

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1900’s

1925: Schrödinger Equation proposed

1929: Dirac’s proposal to simulate chemical systems

1935: The EPR Paradox, a thought experiment designed to demonstrate an inherent paradox in the early formation of quantum theory, later becomes the best-known example of quantum entanglement

1964: Bell’s Theorem

1965: Feynman theories on quantum electrodynamics

1980

1981: Feynman proposes quantum phenomenon to perform computation

1984: IBM’s Quantum Cryptography

1985: David Deutsch described first universal quantum computer

1994: P. Shors’ prime factorization algorithm

1996: Grover’s database search algorithm

1998: First working two-qubit quantum computer demonstrated

2001: A seven-qubit experiment conducted to factor the number 15

2010

2010: D-Wave commercial quantum computing facility

2016: IBM’s QPU availability on cloud for R&D experiments

2017
1. D-Wave’s 2000Q system for commercial use
2. IBM’s first 50Q QPUs
3. Google’s QC packages for Chemistry
4. Microsoft’s QC programing languages

2018
1. Intel’s 49Q chip development
2. Google-Cirq

2019
1. Google Sycamore claimed quantum supremacy
2. IBMQ’s first commercial 20-qubit system

2020: Chinese scientists claimed Jiuzhang achieved another quantum supremacy

2021: IBM's Eagle Processor

2024: Google's Willow Processor

2025

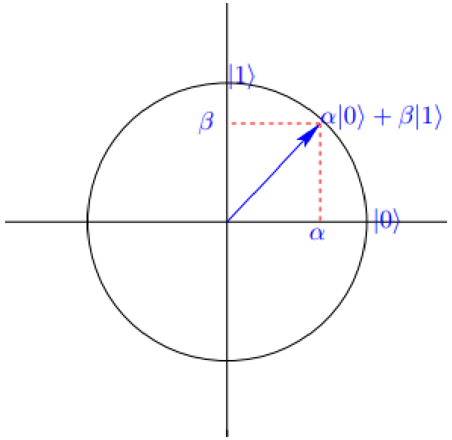
2025: Amazon's Ocelot Chip and Industry Growth

2025: The UN declares Internation year of QST

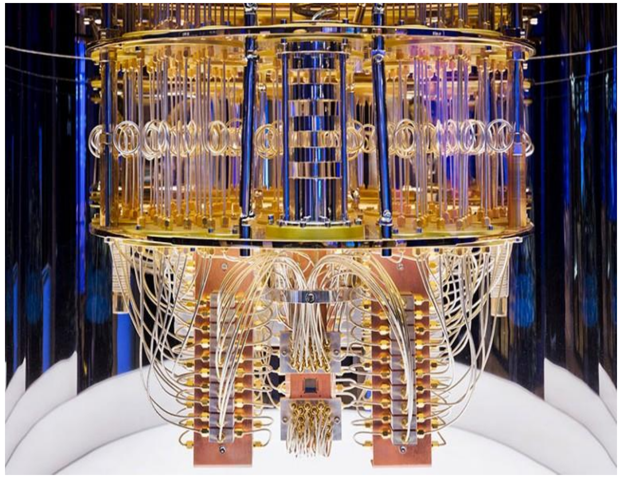
Quantum Computer

- A computer that uses the laws of quantum mechanics to perform massively parallel computing through the principles of *superposition, entanglement, and decoherence*
- The smallest unit of information in a quantum computer – Quantum bit or Qubit
- A qubit may be in the "on" (1) state or in the "off" (0) state: $|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle$, $|\alpha|^2 + |\beta|^2 = 1$,

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



A single-qubit visualization as a unit vector on the plane

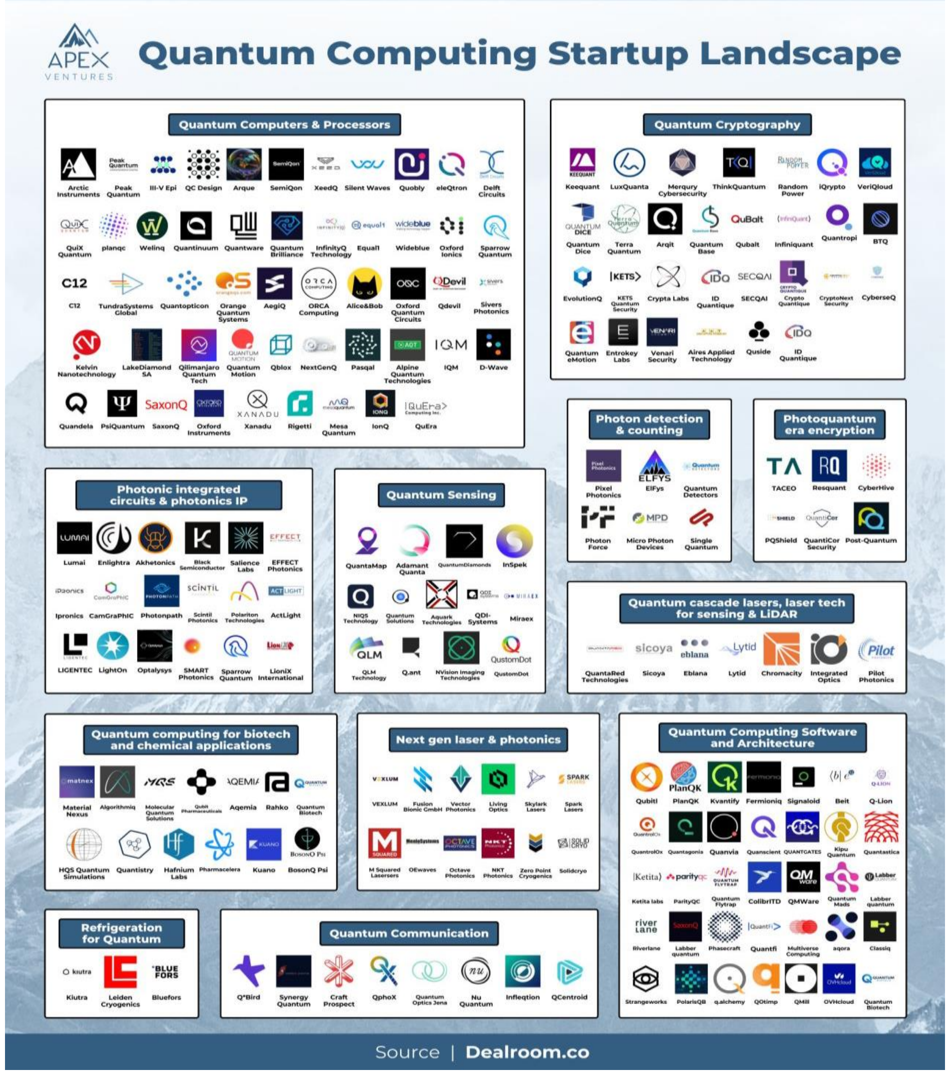


IBM Quantum Computer
Superconducting device: 153 qubits

IonQ Quantum Computer
Trapped ion device: 36 qubits

IQM Quantum Computer
Superconducting device: 150 qubits

Growth & Investment Landscape



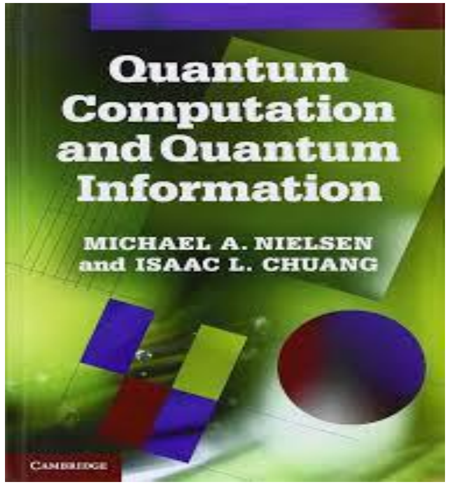
Bits & Qubit

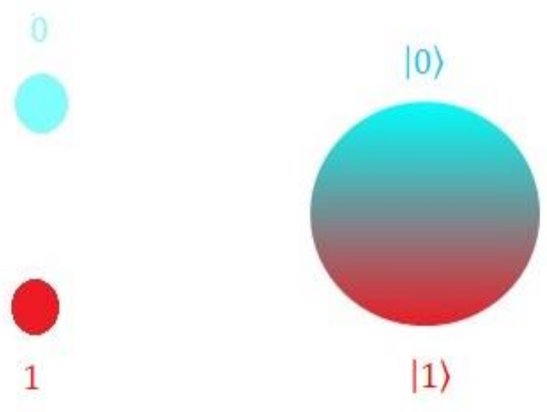
Classical bits:

- It can be in two distinct states, 0 and 1
- It can be measured completely
- It can not be changed by measurement
- It can be copied and erased

Quantum bits (Qubits):

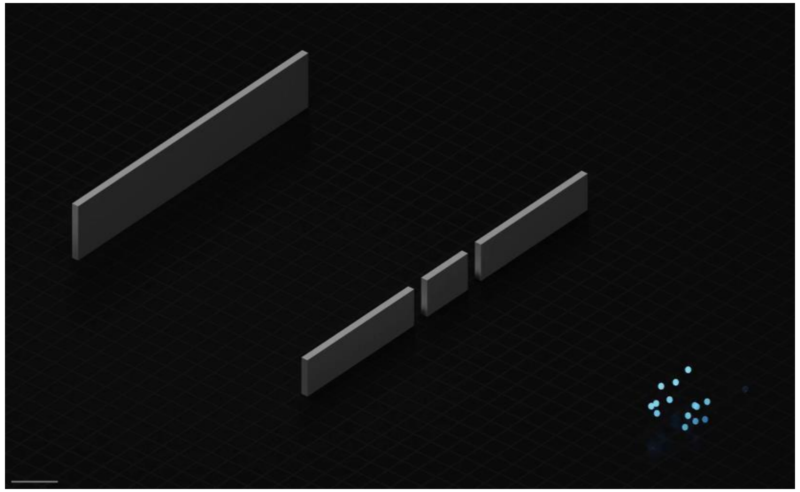
- can be in state $|0\rangle$ or in state $|1\rangle$ or in any other state that is a linear combination of the two states
- It can be measured partially with given probability
- It can be changed by measurement
- It can't be copied and erased



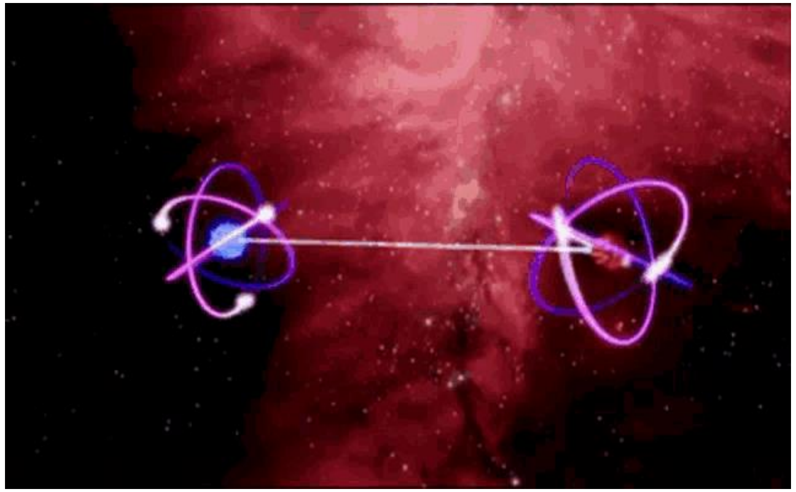


Quantum Principles

- Superposition
  - A quantum state is in a linear combination of other distinct quantum states, forms a new quantum states
  - Superposed states measure in equal probability
  - Provides $parallelism$ (multiple operations simultaneously)



- Entanglement
  - A pair of particles is entangled when the quantum state of each particle cannot be described independently of the quantum state of the other particle
  - Entanglement can't be shared no matter how far they are apart
  - Enables strong correlation between the particles
  - Enables $speed-up$ (allows for faster algorithm - *Shor*)



Gates & Circuit

- Quantum states ∈ *Hilbert space*, form *complex vector spaces* (follow tensor algebra rules)
- Quantum computation uses quantum gates
  - ➢ Pauli gates (X/Y/Z) *
  - ➢ Hadamard gate**
  - ➢ CNOT gate ***

*

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

$$Y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}$$

$$Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

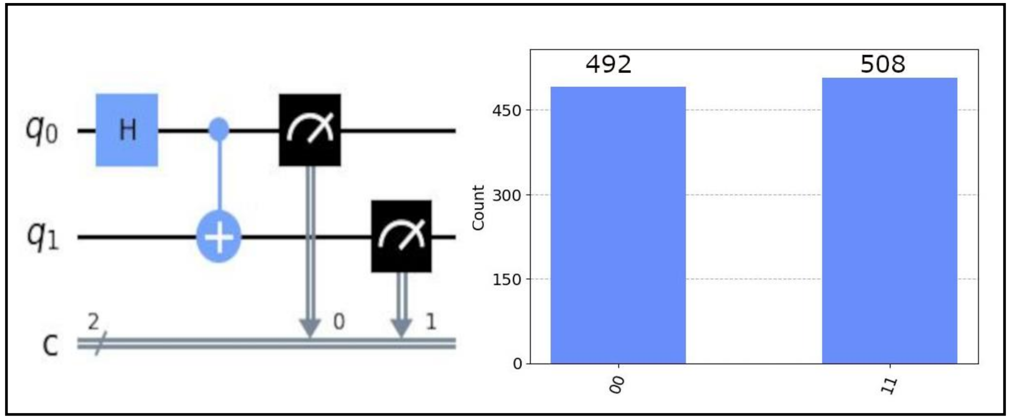
**

$$H = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

***

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

- $H|0\rangle = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}} (|0\rangle + |1\rangle)$
- $CNOT\left(\frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \otimes \begin{pmatrix} 1 \\ 0 \end{pmatrix}\right) = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ \frac{1}{\sqrt{2}} \\ 0 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ 0 \\ \frac{1}{\sqrt{2}} \end{pmatrix}$
- Quantum gates are unitary and reversible $\left(UU^{\dagger} = I\right)$
- Rotation operators: $R_X(\theta) = e^{-\frac{i\theta}{2}X}, R_Y(\theta) = e^{-\frac{i\theta}{2}Y}, R_Z(\theta) = e^{-\frac{i\theta}{2}Z}$



A 2-qubit quantum circuit consists of a H-gate, a CNOT-gate, and a measurements operator, and the circuit result.

Famous Quantum Algorithms

Algorithms	Applications	Potential application field
Shor’s Algorithm	RSA decryption	Cryptography
HHL Algorithm	Inverse transform of a matrix	Machine learning
Grover’s Algorithm	Search problem	Search in unsorted databases
Variational Quantum Eigensolver (VQE)	Eigensolver	Medicine & New material finding
Quantum Approximate optimization Algorithm (QAOA)	Optimization	Financial & Satisfiability problems
Quantum Annealing Algorithm	Optimization	Machine Learning & Financial
Variational Quantum Algorithm/Circuit (VQA/VQC)	Classical-Quantum Models	Healthcare & Machine learning

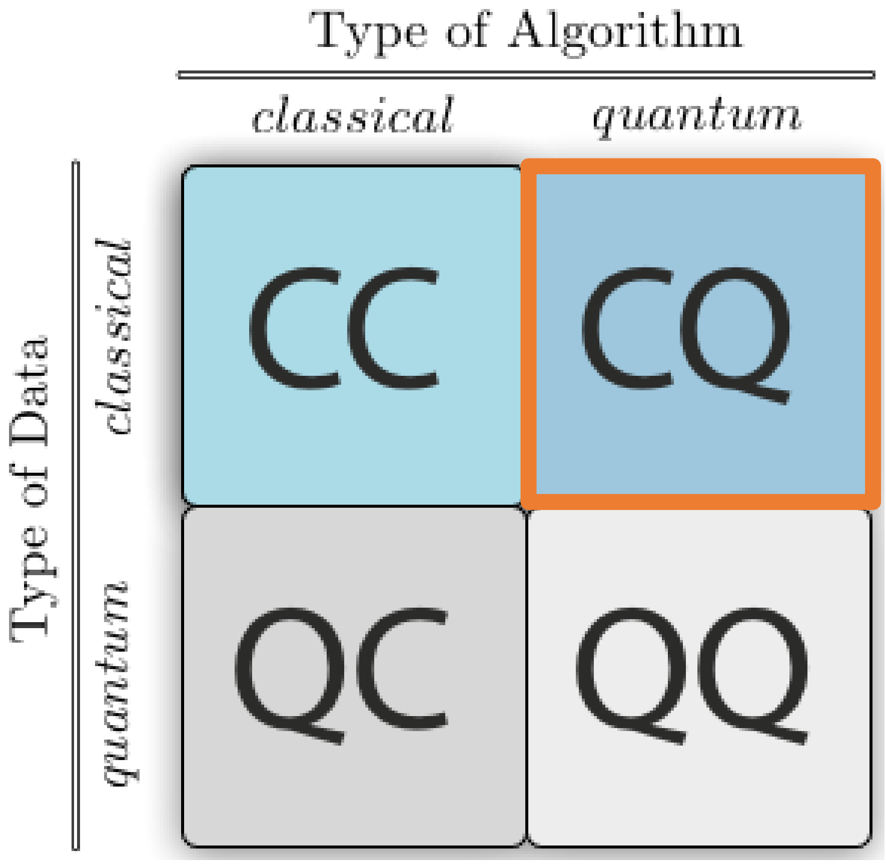
Cho et al., 2021; Jha et al.,2023

Quantum Computing in NISQ Era

NISQ: noisy intermediate-scale quantum (Preskill, 2018)

- Noisy: processors sensitive to their environment
- Scale: quantum processors up to 1000 qubits

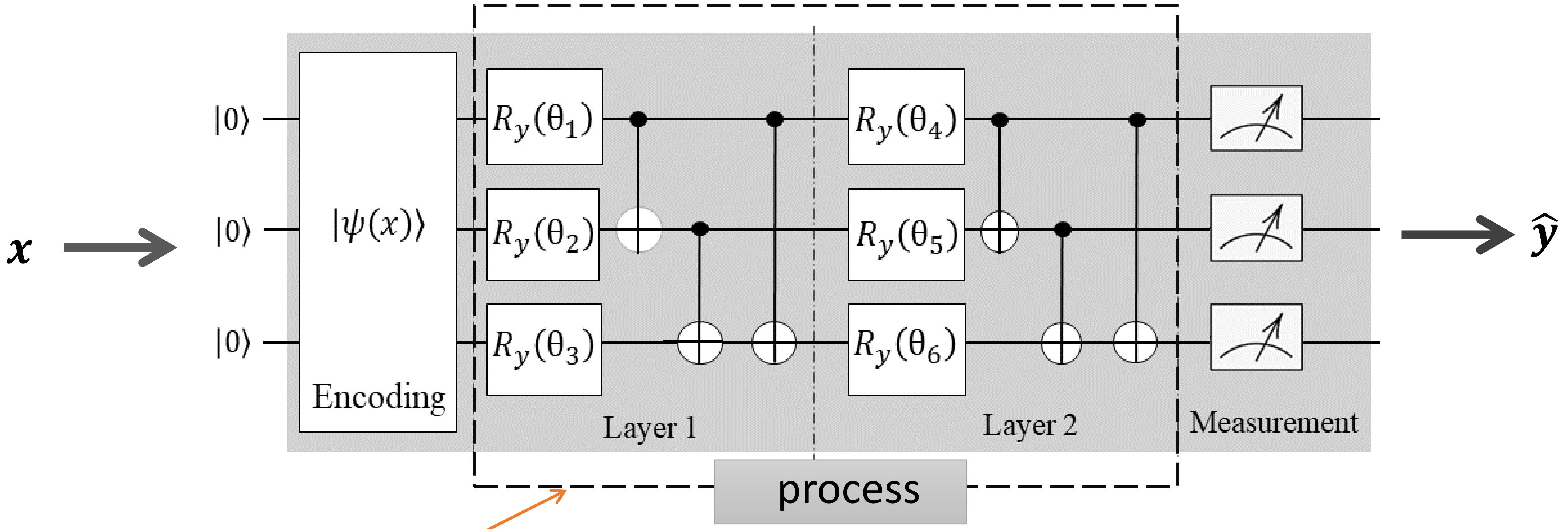
CQ: hybrid classical-quantum model!



https://en.wikipedia.org/wiki/Quantum_machine_learning

Hybrid CQ Approach: VQC

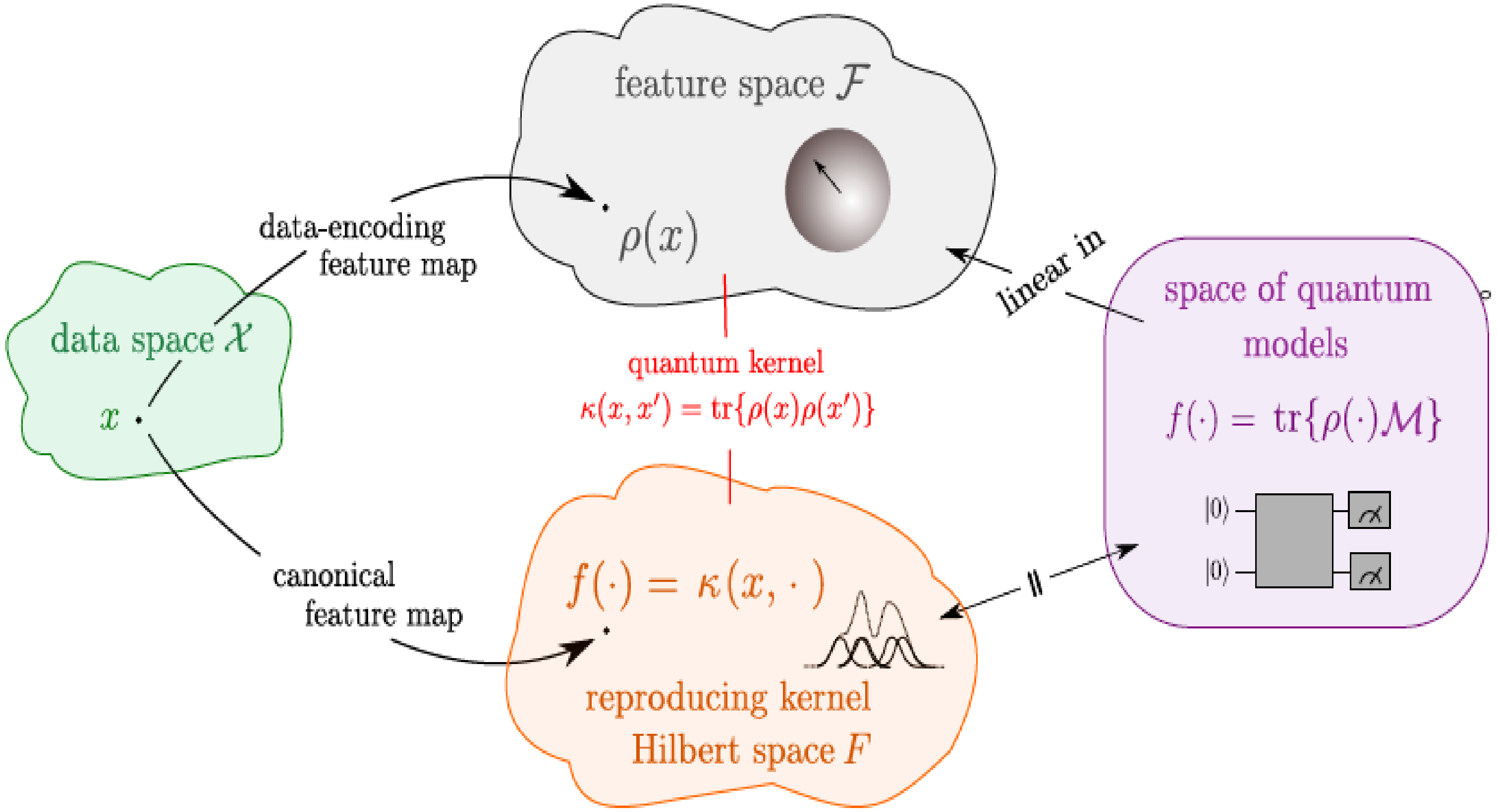
- A variational quantum circuit design for CQ implementations



- Ansatz parameters are trainable

Mitarai et al., 2018; Cerezo et al., 2021

Quantum Kernel



arXiv:2101.11020

- Kernel: encode inputs from lower to higher dimensional feature space
- There exists a direct mathematical link between quantum models and kernel methods
- Kernel method: access to the feature space is facilitated through kernels or inner products of feature vectors
- Quantum kernel: access to the *Hilbert* space of quantum states is given by measurements process, which can also be expressed by inner products of quantum states

Quantum Kernel Implementation

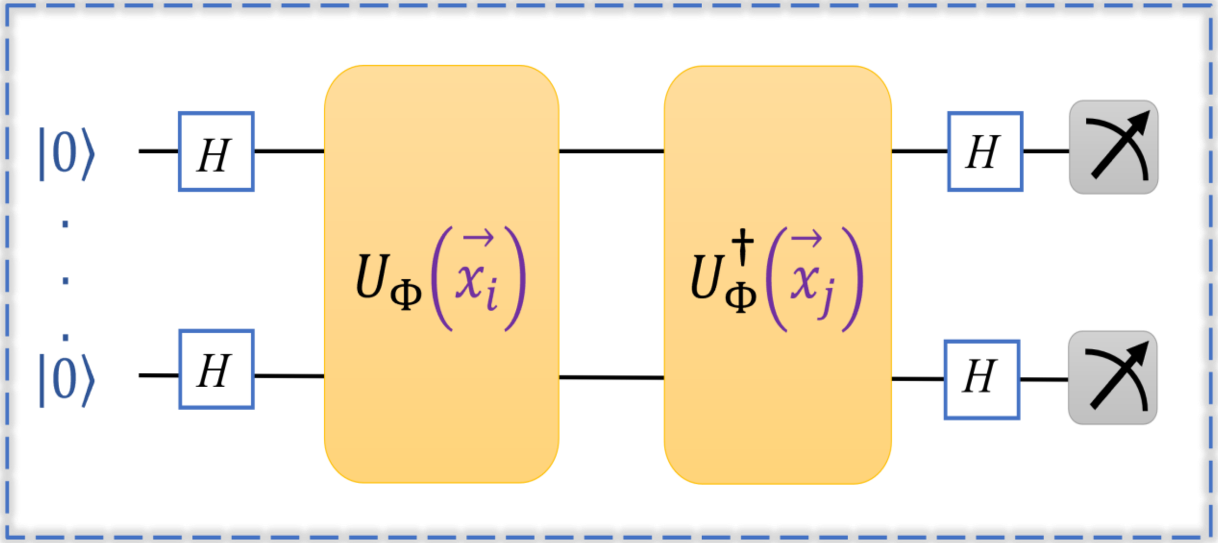
- Data encoding: process to encode classical input into the quantum state space using a quantum feature map
- The choice of feature map is crucial and varies on the datasets provided
- Data-encoding of input vectors $(\vec{x})$ into quantum states,
- $\left|\psi\left(\vec{x}\right)\right\rangle = U_{\Phi}(\vec{x})H^{\otimes 2}U_{\Phi}(\vec{x})H^{\otimes 2}|0\rangle^{\otimes 2}$
- The unitary transformation $U_{\Phi}\left(\vec{x}\right)$ is given by,

$$U_{\Phi}\left(\vec{x}\right) = \exp\left(\mathrm{i}\sum_{j=1}^{n} \alpha_j \phi_s\left(\vec{x}\right)\Pi\sigma_j \in \{I, X, Y, Z\}\right),$$

where $\Phi(x) = \{\phi_1(x), \phi_2(x), \phi_{1,2}(x)\}$

- σ_j and α_j represent key hyperparameters and play an important role in enhancing kernel performance

QKE: $\left|\left\langle\psi\left(\vec{x}_i\right)\middle|\psi\left(\vec{x}_j\right)\right\rangle\right|^2 = \left|\left\langle 0^{\otimes}\middle|U^{\dagger}\left(\vec{x}_i\right)\middle|U\left(\vec{x}_j\right)\middle|0^{\otimes}\right\rangle\right|^2$



Havlíček et al., 2019

Feature Maps

- A *novel feature map* designed to encode the data into a quantum state space as:

$$F_1: \quad \phi_{\{i=1=2\}}(x) = x_i \quad and \quad \phi_{\{1,2\}}(x) = \frac{\pi}{(1+cos(x_1))\,(1+cos(x_2))}$$

Jha et al., 2025

- Suzuki et al., (2020) proposed *five distinct* feature map:

$$F_2: \ \phi_{\{i\}}(x) = x_i \ and \ \phi_{\{1,2\}}(x) = \pi x_1 x_2$$

$$F_3: \ \phi_{\{i\}}(x) = x_i \ and \ \phi_{\{1,2\}}(x) = \frac{\pi}{2}(1 - x_1)(1 - x_2)$$

$$F_4: \ \phi_{\{i\}}(x) = x_i \ and \ \phi_{\{1,2\}}(x) = exp\left(\frac{|x_1 - x_2|^2}{\frac{8}{ln(\pi)}}\right)$$

$$F_5: \ \phi_{\{i\}}(x) = x_i \ and \ \phi_{\{1,2\}}(x) = \frac{\pi}{3\,cos(x_1)\cos(x_2)}$$

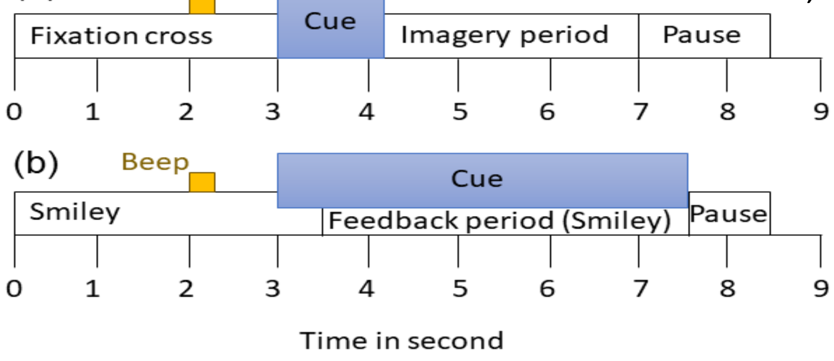
$$F_6: \ \phi_{\{i\}}(x) = x_i \ and \ \phi_{\{1,2\}}(x) = \pi cos(x_1)\cos(x_2)$$

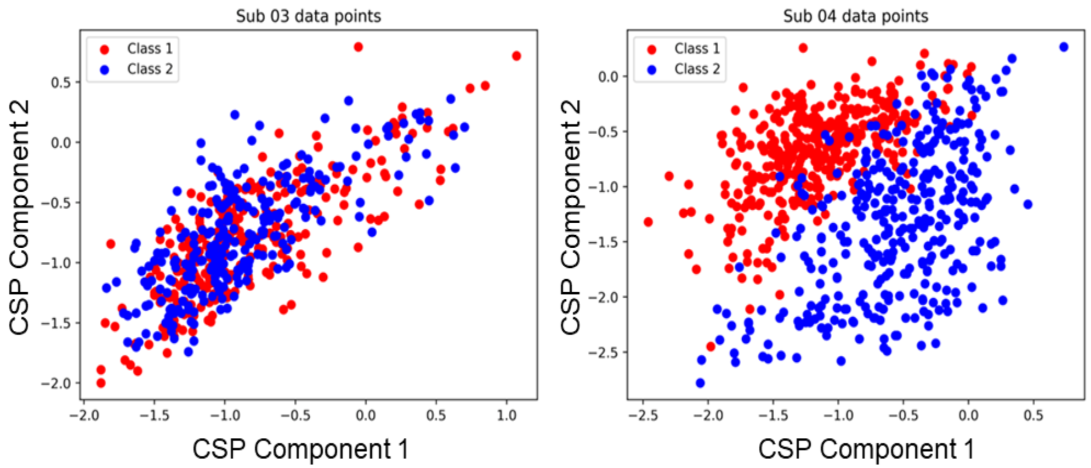
Suzuki et al., 2020

A Case Study with EEG-BCI Data

- BCI Competition IV dataset 2(b) is an open datasets with three bipolar *EEG channels* $\{C3, CZ, C4\}$
- The data experiment included *9-subjects* for two motor imagery tasks: *LH & RH movement*
- All five-sessions data were used with preprocessing and two CSP components were used for binary classification

Leeb et al., 2020

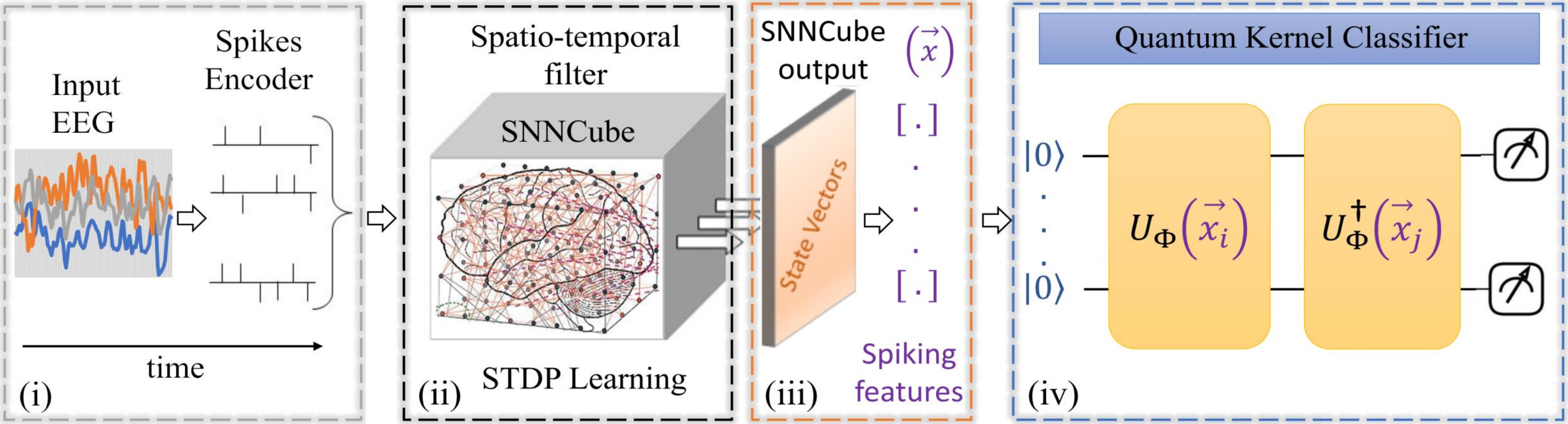




Jha et al., ICONIP 2024

Sub	F_1	F_2	F_3	F_4	F_5	F_6	SVM_L	SVM_R	NB	LDA
1	69.19	66.30	68.10	**70.46**	63.58	69.93	69.37	69.74	65.76	69.38
2	**59.58**	56.96	59.22	58.36	56.44	59.04	58.87	59.05	56.25	59.39
3	**54.17**	50.95	49.24	51.89	52.67	49.42	51.89	48.86	49.80	52.46
4	**91.08**	87.25	89.23	90.36	88.80	91.07	90.65	90.79	89.37	90.79
5	70.68	70.53	**71.14**	70.22	67.02	70.68	70.07	69.92	67.32	69.46
6	78.95	73.08	75.84	**79.31**	77.84	77.48	78.94	78.77	78.21	78.94
7	66.15	67.51	66.32	68.02	67.35	67.51	67.51	68.02	**68.37**	67.00
8	77.59	72.94	76.51	77.95	74.19	77.76	76.88	**77.94**	74.36	76.15
9	78.29	76.88	76.86	77.40	74.72	**79.79**	76.51	78.11	73.30	77.04
Avg	**71.74**	69.15	70.27	71.55	69.17	71.40	71.18	71.24	69.19	71.17

A Hybrid SNN-QC Model



(i) input EEG signals are transformed into spike trains

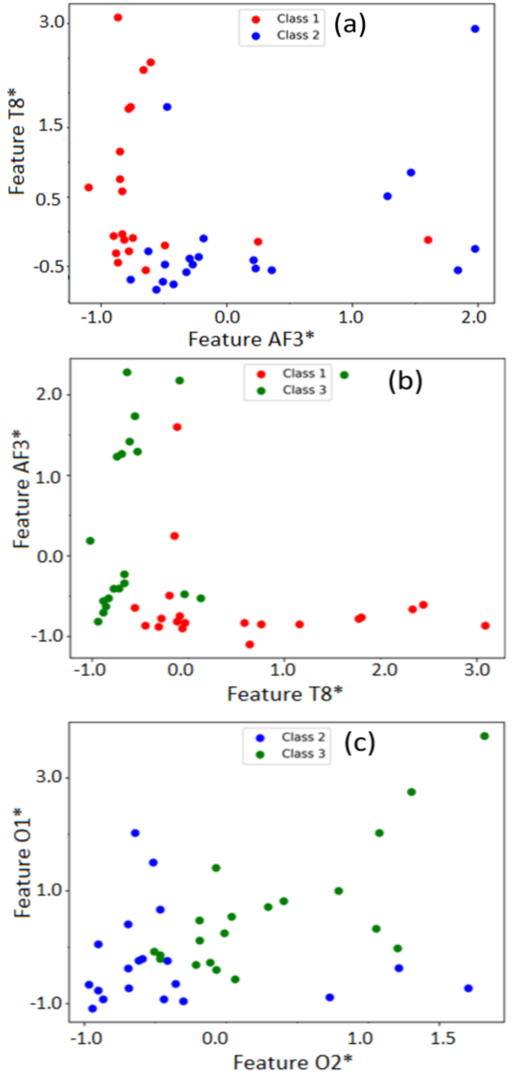
(ii) spikes are mapped onto a spatiotemporal filter (SNNCube) using known locations (i.e. EEG channels locations) and learned synchronously

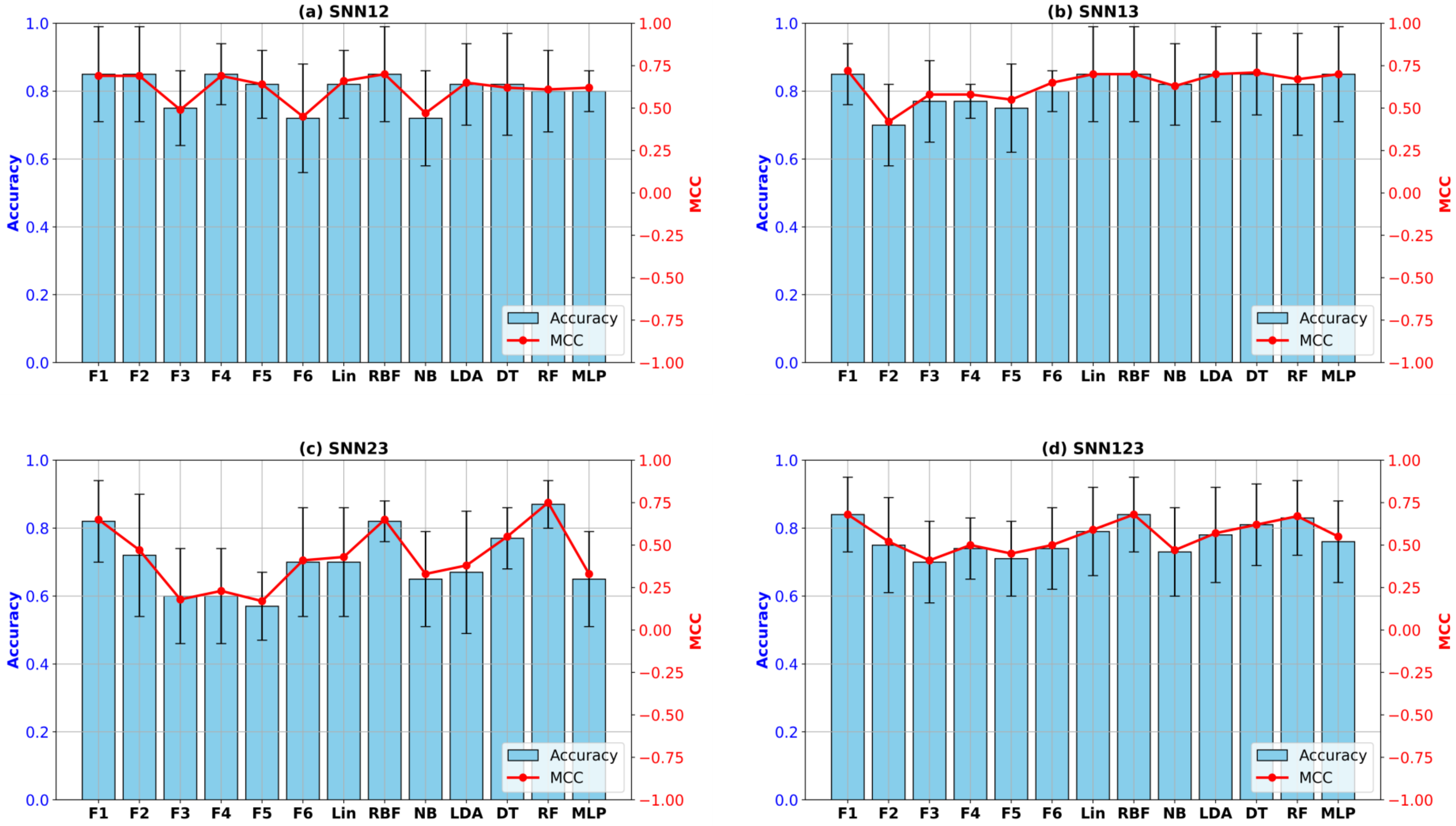
(iii) an output module provides trained spiking features in the form of spike frequency state vectors

(iv) these spiking features are used as input vectors to quantum kernel classifiers

Kasabov, 2014; Jha et al., 2025

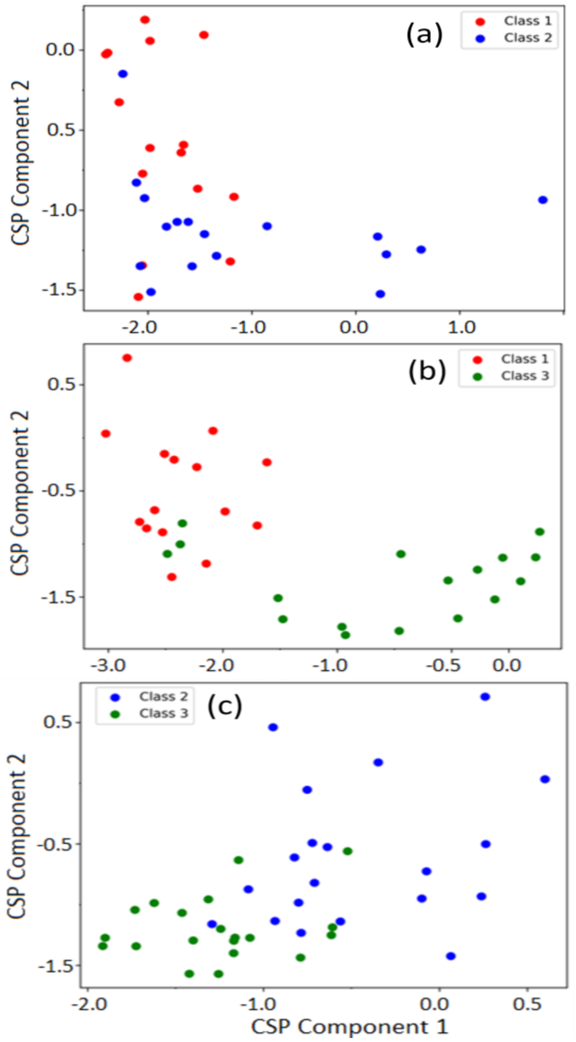
SNN-QC Results

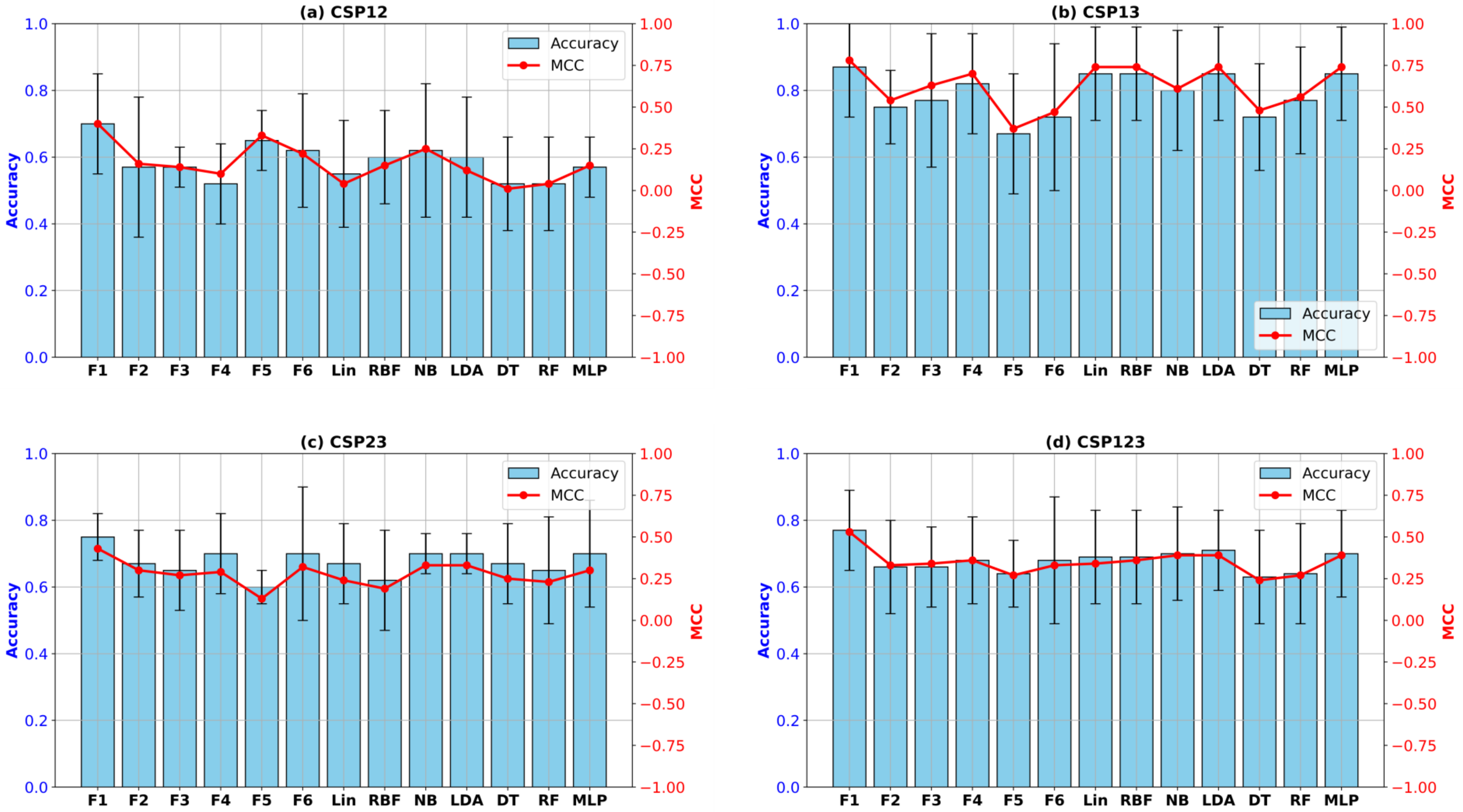




Jha et al., 2025

Results…

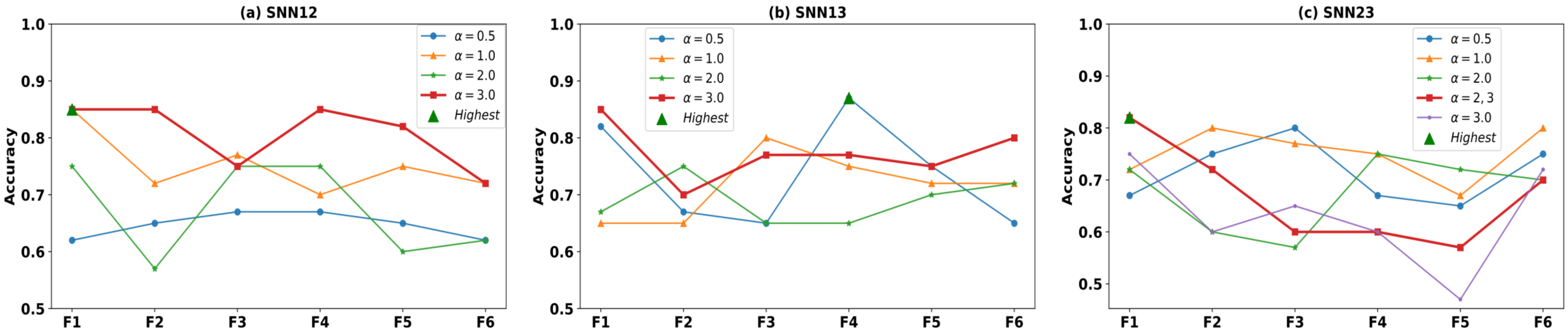




Jha et al., 2025

Hyperparameter Analysis

- Hyperparameter analysis: the impact of tuning α-hyperparameter on the classification performance of spike frequency state vectors

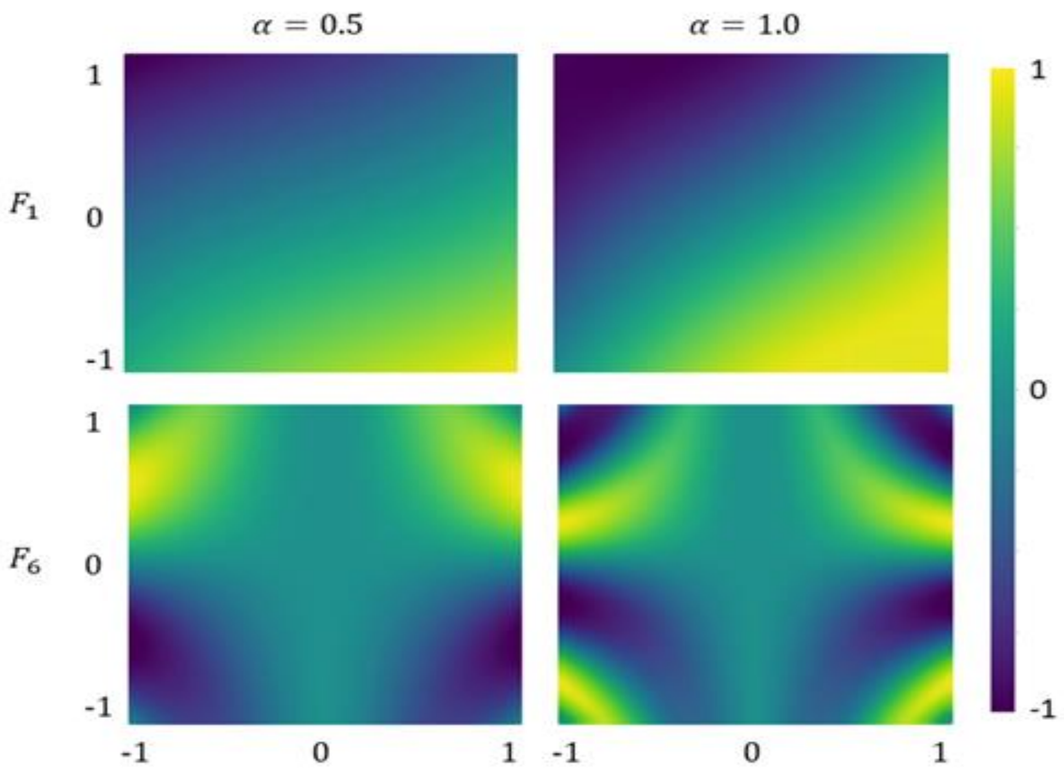


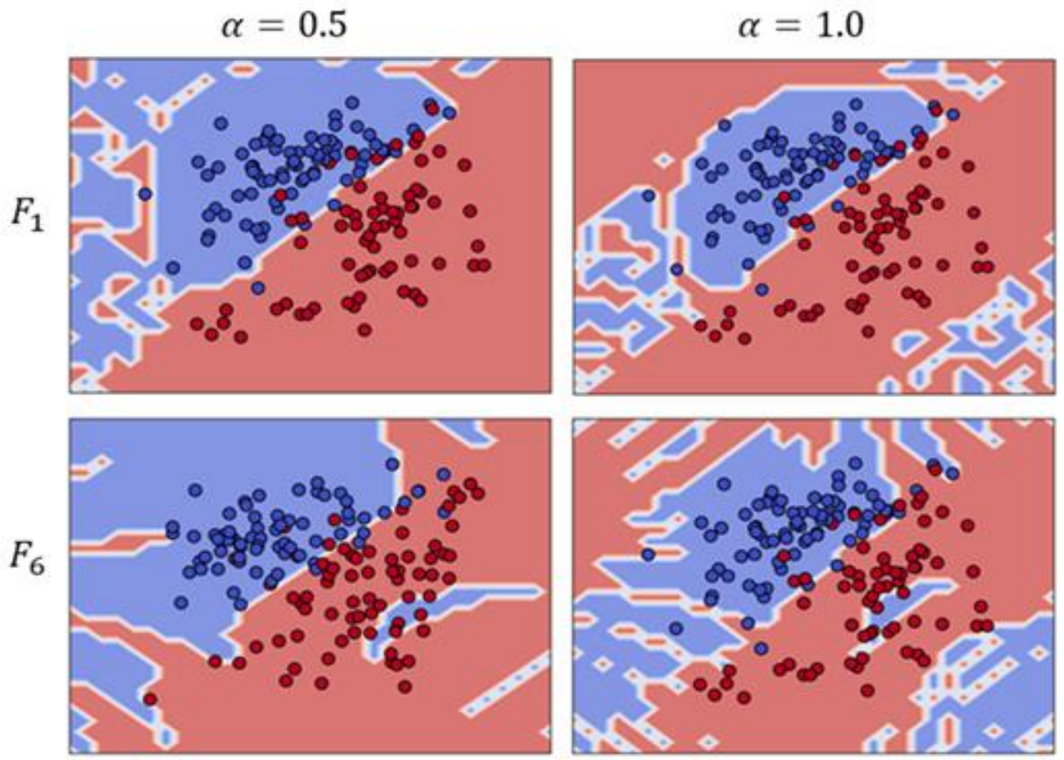
Jha et al., 2025

Feature Map & Decision Boundary

- Feature maps can capture *complex patterns* in datasets
- They provide an *initial prediction* of how an encoding function may impact data classification

- Quantum kernels facilitate the formulation of *suitable and complex hyperplanes*
- With appropriate hyperparameter tuning, QKE can lead to more *expressive decision boundaries*





Jha et al., ICONIP 2024

Result Highlights

- Hybrid classical–quantum models can be useful for developing *quantum-enhanced classification methods*, such as SNN-QC, other classifiers
- Feature maps are capable of capturing *complex patterns* in datasets
- Quantum kernels exhibit *complex decision boundaries*, resulting in improved classification performance
- With proper *hyperparameter tuning*, the performance of quantum kernels can be significantly enhanced
- Future work will focus on utilizing additional datasets to *generalize* the presented findings and to further explore hyperparameter sensitivity
- There is significant potential for expanding the future applications of Quantum ML to solve complex, and real-world problems
- The generalization of encoding functions remains a challenge and warrants more in-depth analysis

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Concluding Remarks

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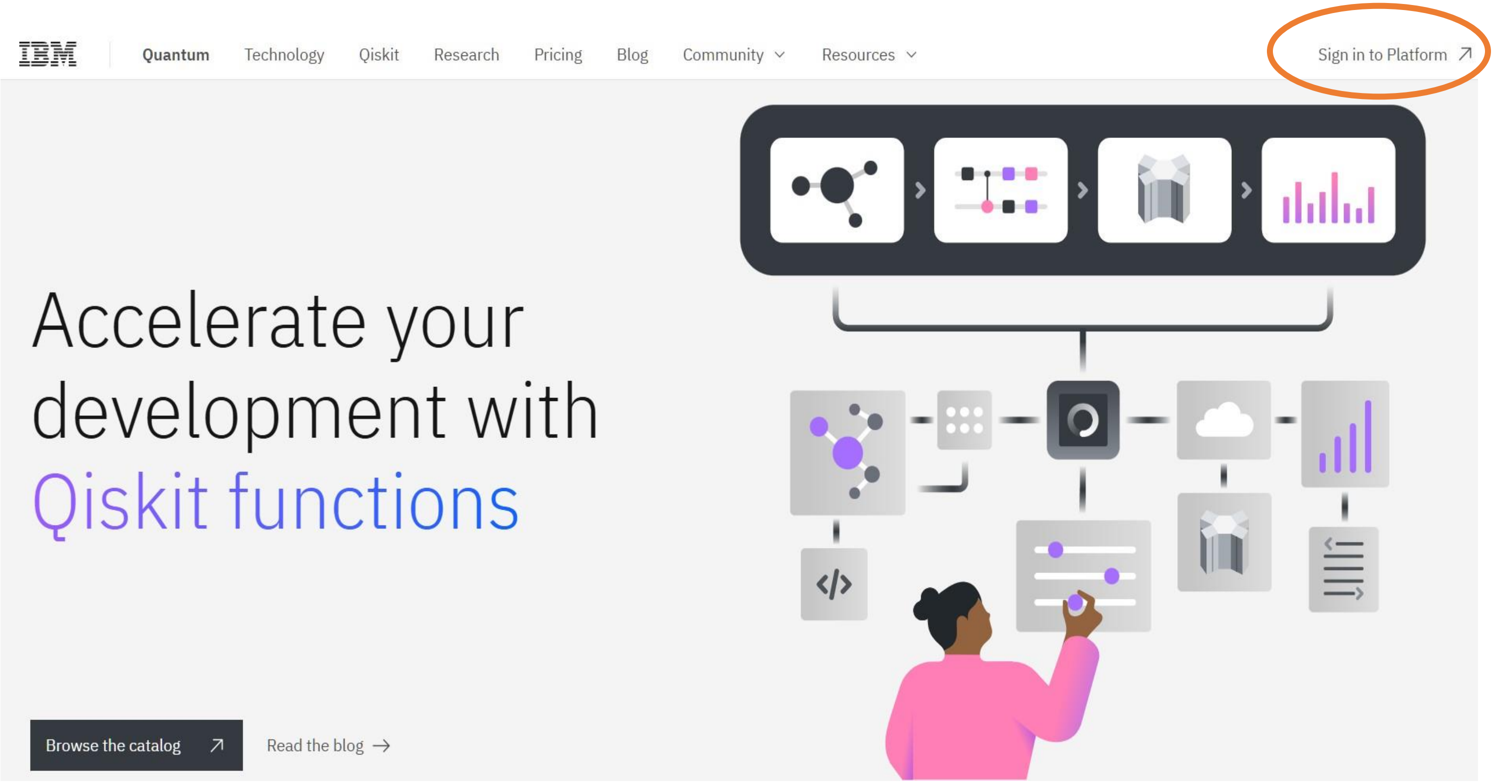
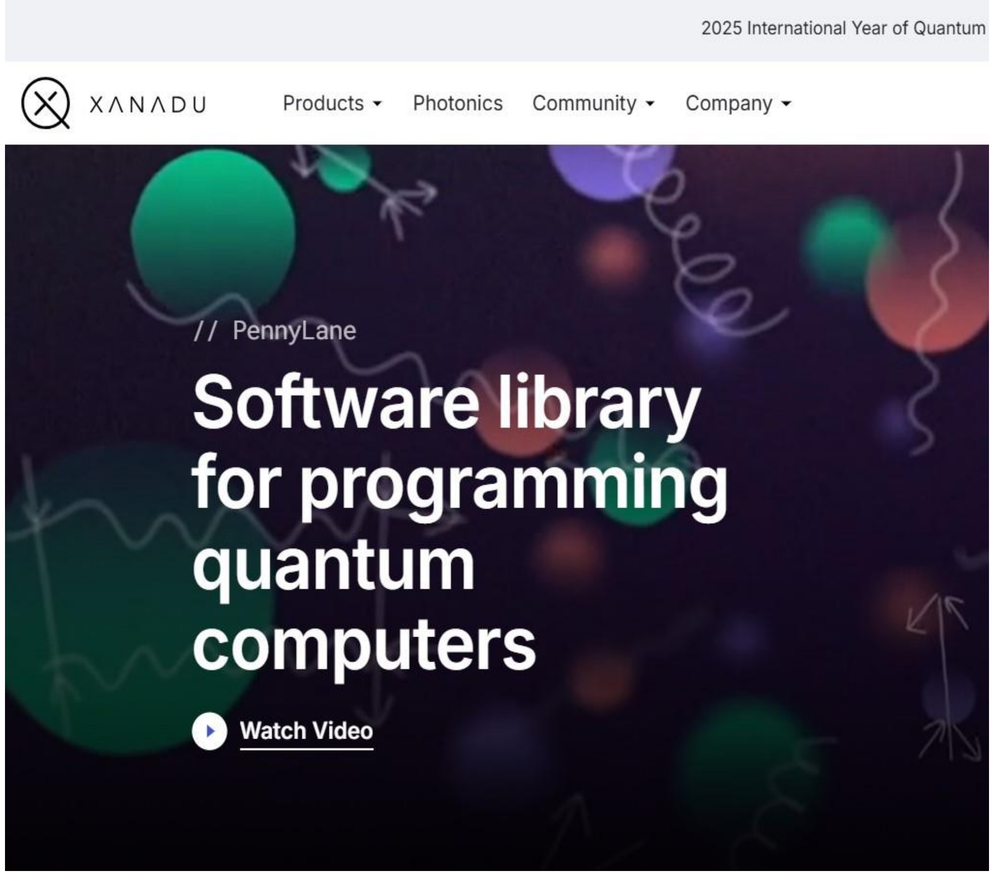
- Algorithm: Hybrid algorithms can be seen as complementary to one another, thereby enhancing the potential of quantum computing for machine learning applications

- Technology: Quantum Processing Units (QPUs), once fully developed and operational, could be highly influential and energy-efficient. Some early case studies already support this hypothesis, albeit on a small scale

Resources: Open Source



https://www.ibm.com/quantum



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Thank you for your attention!

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