Newsletter issue 12-2026, Mar. 21, 2026
AI and Quantum Research Center (AIQRC), Asia University, Taiwan

Activities

[1] We successfully had a proposal accepted for the Fujitsu Quantum Simulator Challenge 2025–26 event. Click here for more information.

[2] We recently secured approval for five Ministry of Education–funded programs in Taiwan, creating valuable learning pathways for young people. These programs support international exchange and advanced training at globally recognized universities, helping students build interdisciplinary knowledge, research skills, and global perspectives in fields such as artificial intelligence, quantum computing, biomedical science, systems medicine, and robotics.
Click here for more information.

I-9-10		IBM量子夢：紐約研習營	美國紐約	(九)科技網絡及數位服務	制霸IBM量子科技巔峰	115 年 7 月 13 日至 7 月 28 日，共計 16 日（含飛行日）
I-9-11		醫工量子：UCLA 菁英計畫	美國加州洛杉磯	(九)科技網絡及數位服務	探索腦科學與量子計算	115 年 7 月 6 日至 9 月 3 日，共計 60 日（含飛行日）
I-9-12		量子金融：赴美職涯領航	美國大紐約區	(九)科技網絡及數位服務	跨足量子與AI金融實務	115 年 7 月 6 日至 8 月 9 日，共計 35 日（含飛行日）
I-9-13		AI與石黑浩：探索擬真界	日本大阪	(九)科技網絡及數位服務	台日共創人形機器人新未來	115 年 8 月 1 日至 116 年 1 月 15 日，共計 168 日（含飛行日）
I-9-14		勇闖 WVU：太空機器人實戰	美國摩根敦	(九)科技網絡及數位服務	太空採集機器人見習	115 年 7 月 6 日至 7 月 23 日，共計 18 日（含飛行日）

Quantum Feature Maps for Enhanced Performance in Quantum Kernel Machine Learning

A quantum kernel is an advanced computational technique designed to project classical data into a higher-dimensional feature space, enabling more effective separation of both linear and nonlinear data. At its core, a kernel function measures the similarity between pairs of data points. In the quantum framework, this similarity is evaluated after the data have been encoded into a quantum feature space using a feature map, as shown in Figure 1(a). By leveraging the principles of quantum mechanics, quantum kernels provide a powerful approach to capturing complex patterns and structures within data. The quantum kernel estimation circuit with feature map encoding is shown in Figure 1(b).

By tuning nonlinear encoding functions within the quantum feature map, complex multi-dimensional data can be represented more expressively in quantum Hilbert space. Empirical studies have shown that such nonlinear quantum feature mappings can significantly enhance classification performance and improve predictive accuracy, particularly when handling highly complex, multi-dimensional datasets. As illustrated in Equation (1), a feature map was proposed that allows us to tune the hyperparameters through the rotational factor α and the nonlinear data encoding functions $\phi_s(\vec{x})$. This feature map is given by

$$U_{\emptyset(\vec{x})} = \exp\,(i \sum_{j=1}^{n} \alpha_j\, \phi_s(\vec{x}) \prod P_j) \tag{1}$$

$P_j \in (I, X, Y, Z)$ denote the single-qubit Pauli gates. Data-encoding scale is set by the rotational factor α, along with the Pauli operator choice, can be treated as a hyperparameter that significantly affects the performance of the quantum feature map.

The functions $\phi_s(\vec{x})$ represent nonlinear data-encoding functions used to tune the hyperparameters, defined as follows:

$$F1: \phi_{\{i\}}(x) = x_i \; and \; \phi_{\{i,2\}}(x) = \frac{\pi}{(1+\cos(x_1))(1+\cos(x_2))} \tag{2}$$

$$F2: \phi_{\{i\}}(x) = x_i \; and \; \phi_{\{i,2\}}(x) = \pi x_1 x_2 \tag{3}$$

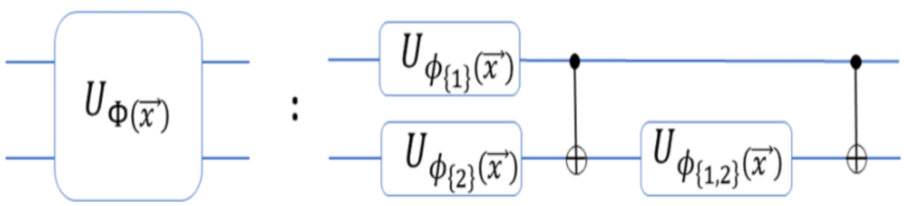
$$F3: \phi_{\{i\}}(x) = x_i \; and \; \phi_{\{i,2\}}(x) = \frac{\pi}{2}(1 - x_1)(1 - x_2) \tag{4}$$

$$F4: \phi_{\{i\}}(x) = x_i \; and \; \phi_{\{i,2\}}(x) = \exp\left(\frac{\frac{|x_1 - x_2|^2}{8}}{\ln(\pi)}\right) \tag{5}$$

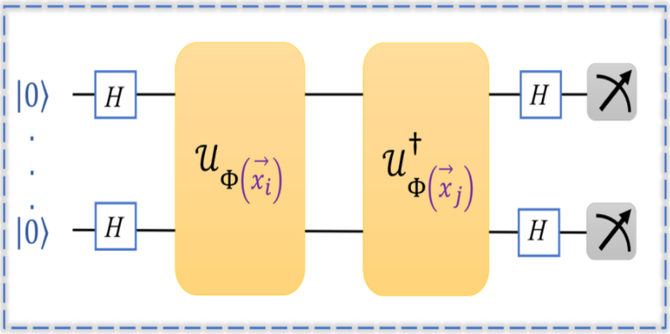
$$F5: \phi_{\{i\}}(x) = x_i \; and \; \phi_{\{i,2\}}(x) = \frac{\pi}{3\cos(x_1)\cos(x_2)} \tag{6}$$

$$F6: \phi_{\{i\}}(x) = x_i \; and \; \phi_{\{i,2\}}(x) = \pi\cos(x_1)\cos(x_2) \tag{7}$$

Jha et al., considered four datasets are used to evaluate the model's performance (Jha et al., 2026): Circle, Moon, XOR, and WBC. Each dataset employs a distinct quantum circuit design tailored to its data characteristics. Across all four datasets, the circuits follow a common structure: single-qubit rotations are applied first, followed by data-dependent ZZ entangling interactions. The rotation axis varies by dataset, X-rotations for Circle and XOR, Y-rotations for Moon, and Z-rotations for WBC, while the entangling scheme remains consistent.



(a)



(b)

Figure 1. (a) Quantum Feature Map Circuit illustrating classical data encoding via the unitary functions $U_{\emptyset(\vec{x})}$, Unitary U, and CNOT Gates. (b) Quantum Kernel Estimation Circuit with Feature Map Encoding, Initialized in $|0\rangle$ states and followed by Hadamard gates for superposition.

The experimental results demonstrate strong performance across all datasets. For the Circle dataset, methods F1, F4, F5, and F6 achieved 100% accuracy with an MCC of 1.00, indicating perfect classification. For the Moon dataset, method F4 obtained 98% accuracy with an MCC of 0.96, demonstrating highly reliable predictions. For the XOR dataset, method F1 achieved 99% accuracy with an MCC of 0.979, reflecting near-perfect performance. For the WBC dataset, methods F1 and F4 achieved 93.67% accuracy with an MCC of 0.866, indicating strong and consistent classification results.

In comparison, the classical model using the RBF kernel achieved the highest overall performance across the four datasets. For the Circle dataset, it obtained 100% accuracy with an MCC of 1.00, matching perfect classification. For the Moon dataset, it achieved 98% accuracy with an MCC of 0.961. For the XOR dataset, the model reached 99% accuracy with an MCC of 0.979. For the WBC dataset, it obtained 93.49% accuracy with an MCC of 0.862.

The α hyperparameter was evaluated across four settings: 0.5, 1, 2, and 3. Varying α values had distinct effects on model performance across datasets. For the Circle dataset, α= 2 achieved the highest accuracy for methods F1, F4, F5, and F6. For the Moon dataset, α= 2 provided better performance for methods F1 and F4. In the XOR dataset, α= 2 achieved high accuracy across all methods F1–F6. Conversely, for the WBC dataset, a smaller value of α= 0.5 resulted in the highest accuracy for all methods F1–F6. The results (Jha et al., 2026) highlight that the proposed method holds significant potential to boost the performance of quantum kernel estimation, enabling more accurate classification of both linear and nonlinear datasets.

Reference

Jha, R. K., Kasabov, N., Bhattacharyya, S., Coyle, D., & Prasad, G. (2026). Comparative performance analysis of quantum feature maps for quantum kernel-based machine learning. *Scientific Reports*, *16*(1), 8142. https://doi.org/10.1038/s41598-026-39392-9

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