亞洲大學
ASIA UNIVERSITY

AI & QUANTUM RESEARCH CENTER

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AI and Quantum Research Center (AIQRC), Asia University, Taiwan

Activities

[1] During February 2026, Asia University formalized a Memorandum of Understanding with a company recognized for its strength in professional services.

[2] We successfully had a proposal accepted for the Fujitsu Quantum Simulator Challenge 2025–26 event.

[3] We recently succeeded in having five proposals accepted by the Ministry of Education.

Quantum Kernels- Applications to EHR with ADNI as a Case Study

1. Introduction

The rapid growth of real-world data in medicine -- particularly from electronic health records (EHRs) and electronic disease regostries -- has opened new avenues for predicting clinical outcomes and advancing precision medicine. Machine learning techniques have been applied extensively to EHR data to modeling disease prognosis and risk prediction, medication adherence, and patient trajectories. However, classical approaches face limitations when confronted with highly complex correlation structures, small sample sizes, or high-dimensional feature spaces. In these regimes, quantum machine learning (QML) has emerged as a promising alternative, with theoretical results suggesting that quantum algorithms can capture patterns that are provably hard for classical methods to learn.

Among the accessible QML techniques is the quantum kernel method. Rather than training a full quantum neural network, quantum kernels leverage a quantum computer to compute a similarity measure (the kernel) between data points, which is then fed into a classical support vector machine (SVM) for classification. This hybrid quantum–classical approach is well-suited to current noisy intermediate-scale quantum (NISQ) devices, as the quantum circuit is used only to evaluate the kernel, while the optimization remains on the classical side.

2. What Are Quantum Kernels?

In classical machine learning, a kernel function measures the similarity between two data points, often by implicitly mapping them into a higher-dimensional feature space where a linear separator can be found. The radial basis function (RBF) kernel, for instance, is widely used in classical SVMs and maps data into an infinite-dimensional space.

A quantum kernel extends this idea by using a parameterized quantum circuit—called a quantum feature map—to encode classical data into the exponentially large Hilbert space of a quantum system. Each data point is mapped to a quantum state, and the kernel value between two points is computed as the inner product (overlap) of their corresponding quantum states. Because the dimensionality of the quantum Hilbert space grows exponentially with the number of qubits, quantum feature maps can access feature spaces that are intractable for classical computation.

The practical workflow is straightforward: a quantum processor computes the kernel matrix for all pairs of training and test samples; this matrix is then passed to a classical SVM solver to find the optimal decision boundary. Crucially, each feature in the dataset maps to one qubit, making the circuit depth manageable for current hardware when the number of features is modest (e.g., 5–20).

3. Why EHR Data?

Electronic health records are rich, longitudinal data sources encompassing demographics, diagnoses, laboratory results, prescriptions, clinical notes, and imaging data. They are increasingly used to generate real-world evidence for drug development, disease management, and health policy. However, EHR-based prediction tasks present several characteristics that align well with quantum kernel methods:

- Complex correlations. EHR data contain intricate temporal and cross-variable dependencies—between lab values, medications, comorbidities, and genetic factors—that may benefit from the expressive power of quantum feature spaces.
- Small cohort sizes. Many clinically meaningful patient subgroups (e.g., rare disease populations, specific treatment cohorts in clinical trials) yield datasets of only a few hundred samples—exactly the regime where quantum kernels may offer advantages over classical approaches.

- Feature-to-sample ratio. When the number of relevant features is relatively large compared to the training set, classical methods often struggle. Quantum kernels operating in exponentially large feature spaces may uncover separability that classical kernels miss.

A landmark study by Krunic et al. [1] provided the first systematic investigation into empirical quantum advantage (EQA) using electronic health record (EHR) data. Working with the Optum de-identified EHR dataset of over 100 million patient lives, the researchers predicted six-month medication persistence for rheumatoid arthritis patients on biologic therapies. They defined a configuration space with 5–20 features and 200–300 training samples and compared quantum SVMs (run on IBM's 27-qubit ibmq_dublin processor) against classical SVMs with RBF kernels. The study identified specific regimes—particularly those with higher feature-to-sample ratios—where quantum kernels matched or exceeded classical performance, representing one of the largest QML experiments on real-world healthcare data to date. It also proposed a generalizable framework that was applied to other EHR cases, such as ADNI.

4. ADNI: A Natural Testbed for Quantum Kernels

The Alzheimer's Disease Neuroimaging Initiative (ADNI) provides an ideal example of the kind of clinical dataset where quantum kernel methods could prove particularly valuable. Established in 2004 as a public–private partnership, ADNI is a landmark longitudinal study designed to develop and validate biomarkers for Alzheimer's disease (AD) clinical trials. Over more than a decade, ADNI has enrolled cognitively normal elderly subjects, patients with mild cognitive impairment (MCI), and patients with early AD across more than 50 sites in the United States and Canada.

ADNI collects a rich, multimodal array of data: structural and functional MRI, PET imaging (amyloid and FDG), cerebrospinal fluid (CSF) biomarkers (Aβ and tau), genetic data (including GWAS and whole-exome sequencing), cognitive assessments, and clinical variables. The successive phases of the study—ADNI-1, ADNI-GO, and ADNI-2—have progressively added new technologies and refined cohort definitions, including early and late MCI subgroups.

Several characteristics of ADNI make it especially relevant for quantum kernel exploration.

- the multimodal nature of the data means that meaningful classification tasks (e.g., predicting and differentiating MCI converters from non-converters) involve combining features from imaging, fluid biomarkers, genetics, and clinical scores—precisely the kind of heterogeneous, high-dimensional feature space that quantum kernels are designed to handle.

- cohort sizes, typically in the hundreds per diagnostic group, which falls within the data regime explored in recent quantum kernel experiments.
- the diagnostic classification challenges in AD particularly the early detection of disease and the prediction of conversion from MCI to dementia—remain difficult even for state-of-the-art classical methods, motivating the search for novel computational approaches.

5. Outlook and Challenges

While the intersection of quantum computing and EHR-based clinical inference research is still in its infancy, the early results are encouraging. The framework established by Krunic et al.—which systematically maps a configuration space of features and samples to identify regimes of quantum advantage—is directly applicable to disease registry like ADNI. The scope of problems addressable by quantum kernel methods is anticipated to grow substantially in near future.

The challenge, which quantum feature map would be best suited to a given dataset remains open. There is no universal prescription yet, and tailoring the circuit design to the data structure shall be an active research area.

For medical applications involving small, complex, and high-dimensional datasets, quantum kernels represent a compelling and increasingly practical tool. Datasets like ADNI, with their rich multimodal structure and well-characterized patient populations, stand to be among the first to benefit from this emerging technology.

References

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