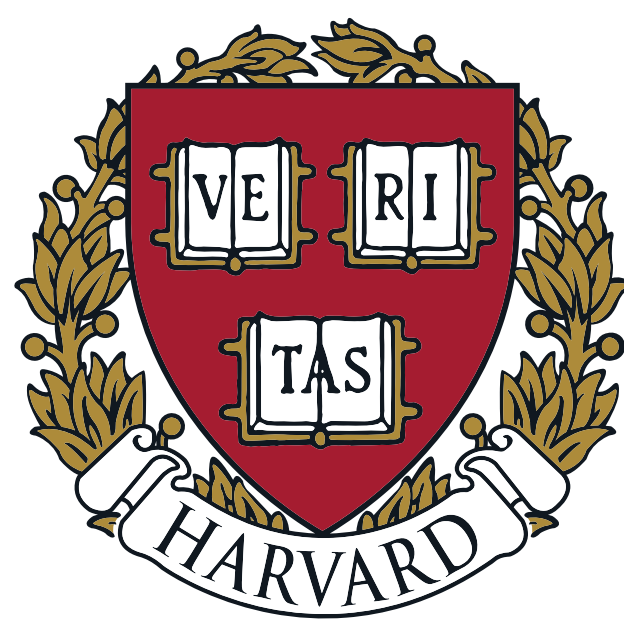
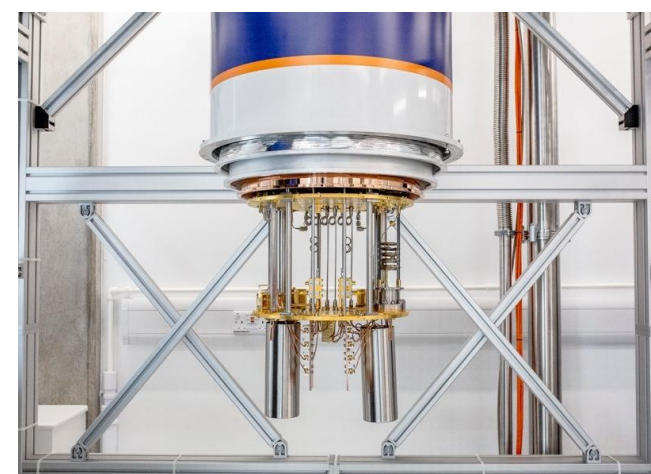




Quantum Product Kernel Methods for Brain Tumor Classification



2026 Quantum Machine Learning REU Program

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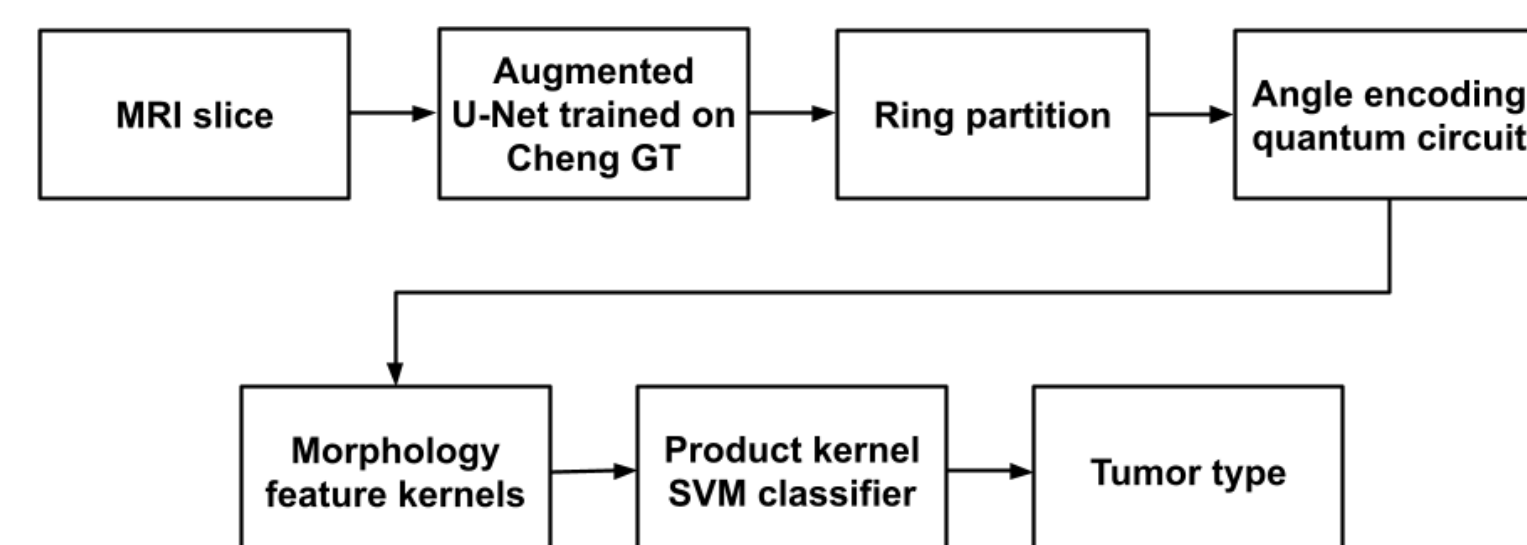


RESEARCH BACKGROUND/DESCRIPTION

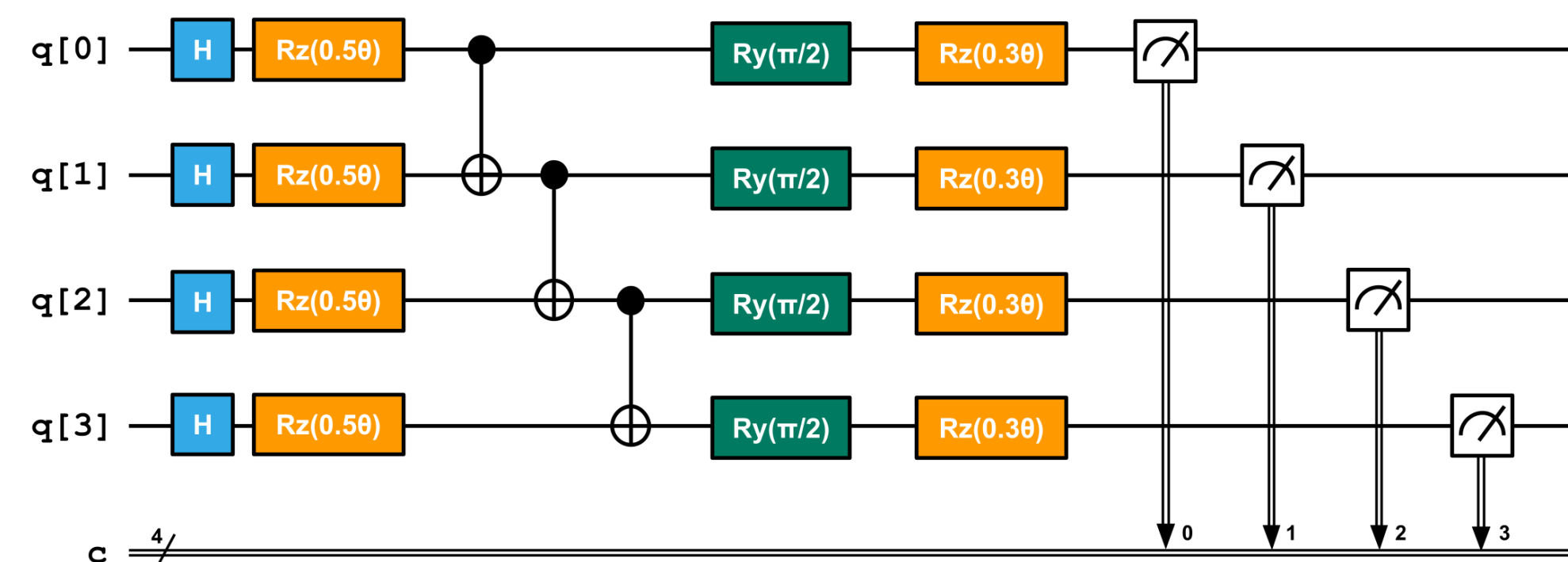
- Nearly 90,000 brain tumors are diagnosed in the United States every year
- We want to classify glioma, meningioma, and pituitary tumors
- Each category exhibits identifiable texture and morphology patterns
- Implementation using AWS Braket

RESEARCH OBJECTIVES/PLAN

- SVM-based classification using fidelity kernels built from quantum feature maps
- Develop five-pipeline model “KPRIME”, adapt model to other datasets via UNet
- Give a theoretical explanation of quantum superiority for product kernel SVMs



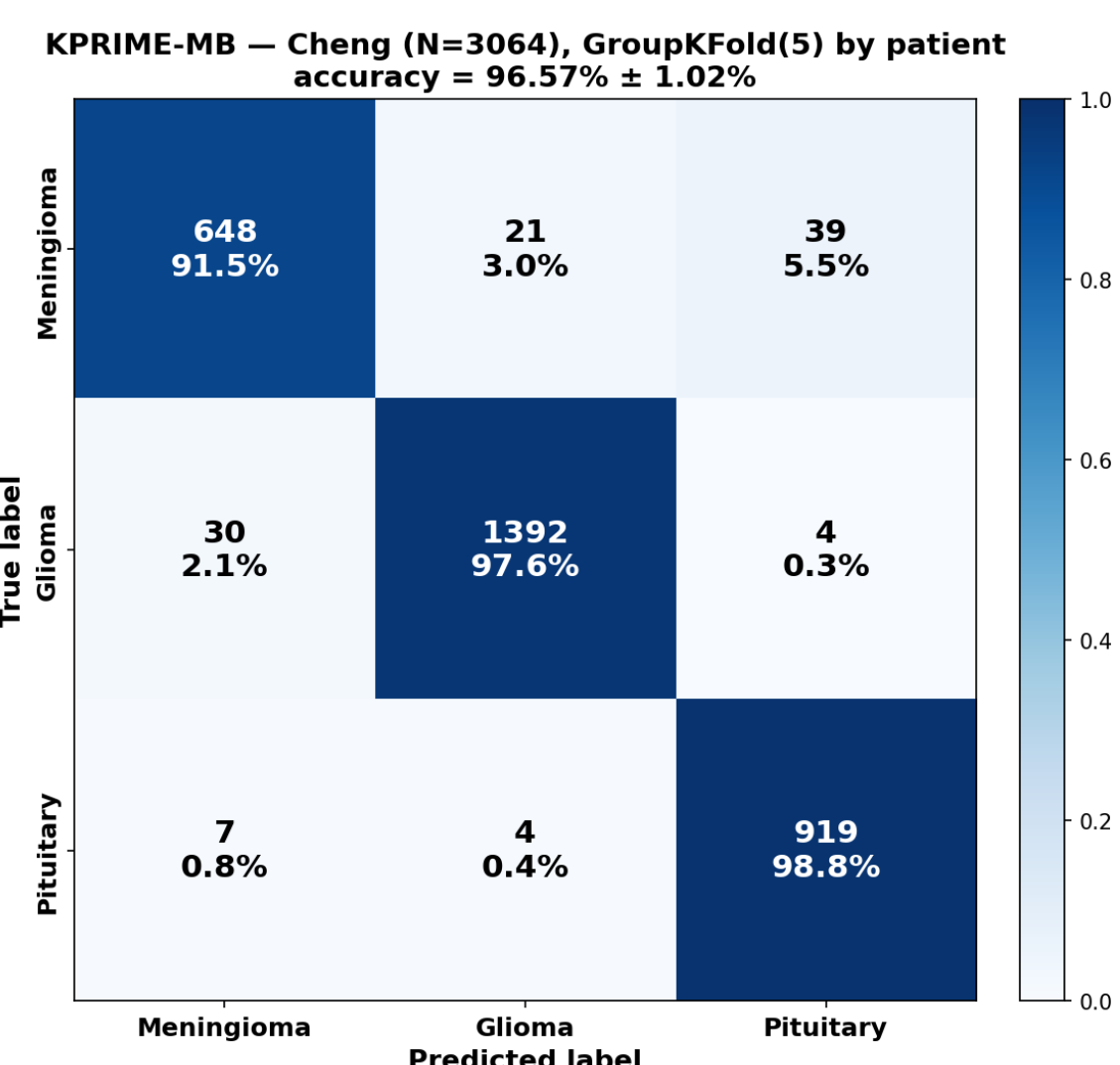
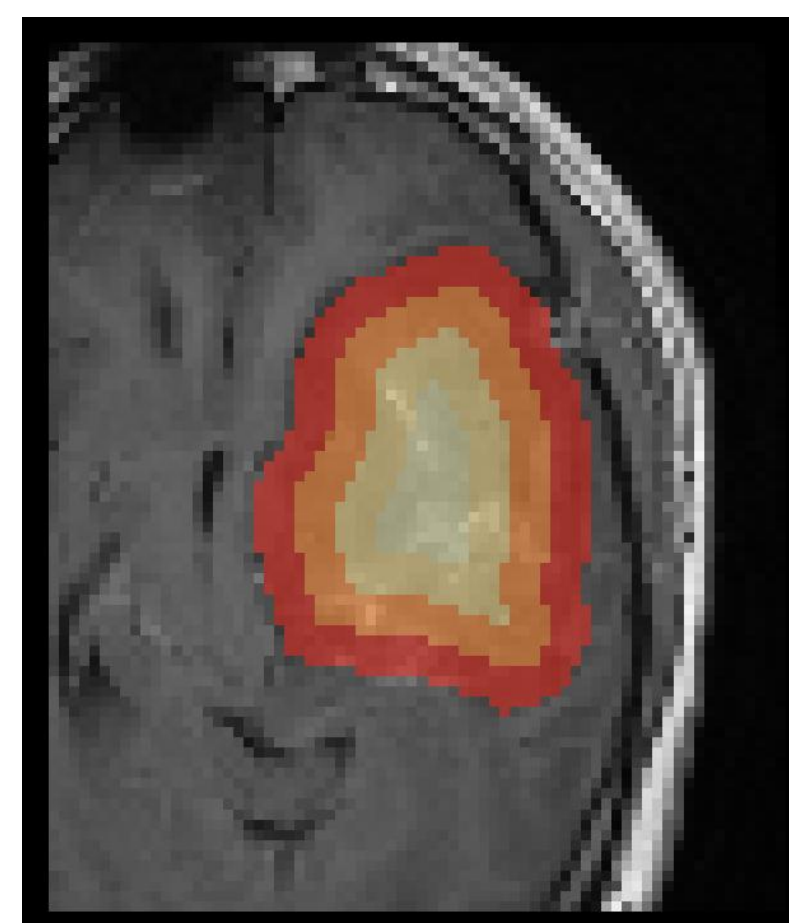
Data-reuploading fidelity kernel (DRU)



METHODS & ALGORITHMS

Baseline model with five pipelines:

- PCA-12 compression of frozen ResNet-18
- Intensity histogram per ring-shaped region
- Texture via gray-level co-occurrence matrix per ring-shaped region
- Tumor centroid coordinates and distance
- Edge sharpness frequencies via Fourier transform of Sobel filter on neighborhood of boundary



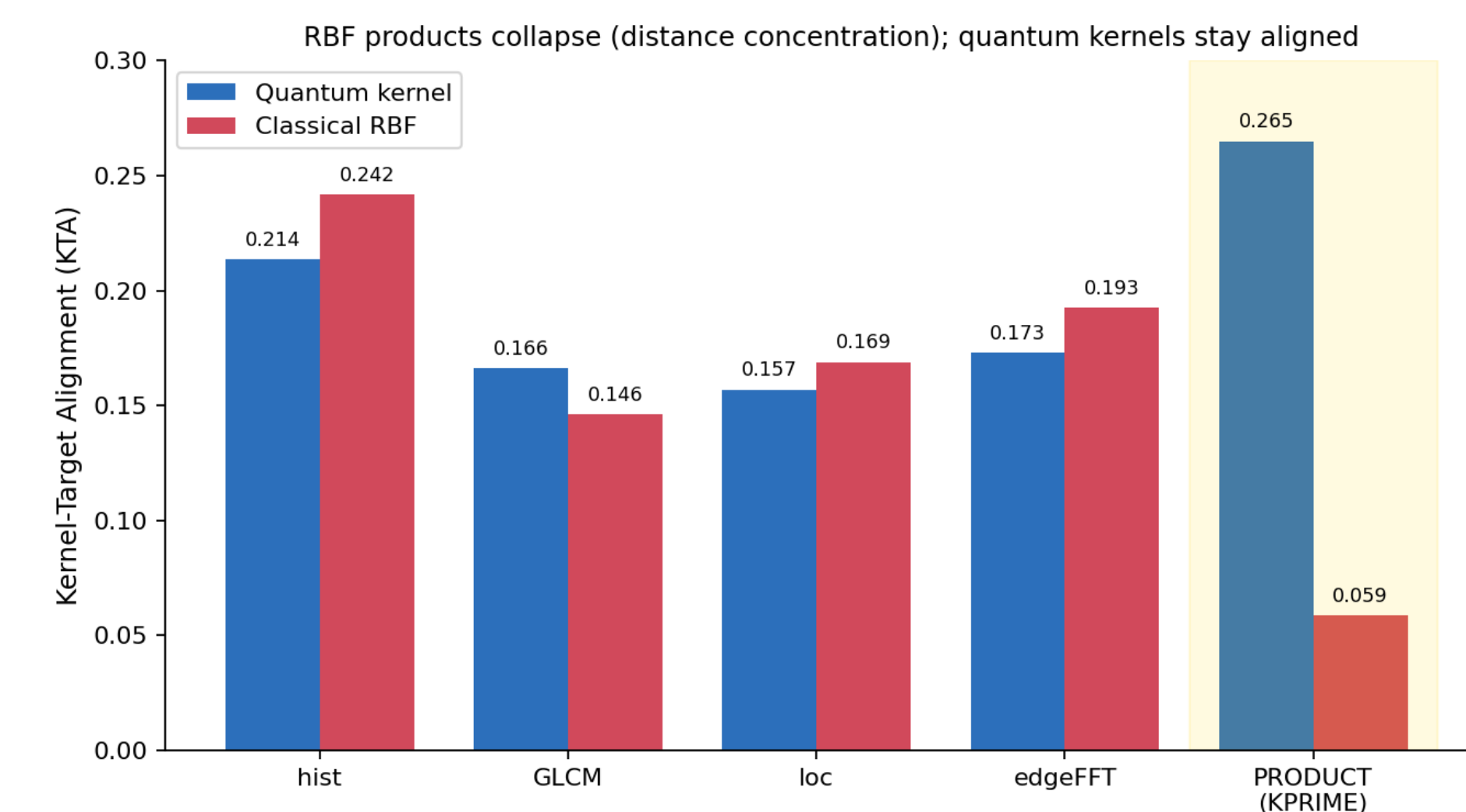
- Example ring-region partition around tumor from contrast-enhanced brain MRI slice [1]

REFERENCES

- [1] J. Cheng, W. Huang, S. Cao, R. Yang, W. Yang, Z. Yun, Z. Wang, and Q. Feng, “Enhanced performance of brain tumor classification via tumor region augmentation and partition,” PLOS ONE, vol. 10, no. 10, Art. no. e0140381, Oct. 2015.
- [2] V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, “Supervised learning with quantum-enhanced feature spaces,” Nature, vol. 567, no. 7747, pp. 209–212, Mar. 2019, doi: 10.1038/s41586-019-0980-2.
- [3] N. A. Babar, J. Lateef, S. Syed, J. Dietlmeier, N. E. O’Connor, G. B. Raupp, and A. Spanias, “Brain tumor classification in MRI scans using edge computing and a shallow attention-guided CNN,” Biomedicine, vol. 13, no. 10, Art. no. 2571, Oct. 2025.

EXPERIMENTAL RESULTS

- Newest model achieves 96.18% patient-level CV accuracy on Cheng
- Quantum product kernels maintain kernel-target alignment as feature blocks are added; classical RBF products collapse
- Results in literature inflated by patient leakage



Dataset (N)	RBF (classical)	DRU only (quantum)	KPRIME (quantum)
Cheng (3064)	0.8205 ± 0.0119	0.8045 ± 0.0175	0.9618 ± 0.0111
Sherif (3611)	0.8773 ± 0.0087	0.8208 ± 0.0071	0.9598 ± 0.0067
Bhuvaji (2764)	0.8155 ± 0.0228	0.7894 ± 0.0220	0.9504 ± 0.0099

CONCLUSIONS & NEXT STEPS

- Quantum product kernels outperform Gaussian kernels (especially for smaller datasets)
- Methodology generalizes well under to other datasets by Sherif et al., Bhuvaji et al.
- Competitive with SOTA models [3] while being quantum-compatible and lower-dimensional
- AWS Braket computational complexity study

