1. Team Name: **NovaQ**

2. Team Participants and Role within the team – All member are technical contributors and researchers.

- Nydia Assaf Aragón - nydia@enluzstrategy.com Founder & Chief Strategist EnLuz Quantum (lead)
- Dhawal Verma dvermaworking@gmail.com PhD in AI, Research Scholar, IIT, Delhi
- Hao Mack Yang - mulliganaceous.ll@mail.utoronto.ca Co-founding CTO, Next Unicorn
- Jasmine Amani Murphy - jaz.ny1618@gmail.com Code Instructor, New York Public Library

3. Team Qualifications for Tackling the Challenge:

Our team members are global hackathon winners and finalists in the areas of AI, ML and advanced quantum algorithm development. Our expertise encompasses graduate level backgrounds in computer science, electronic engineering, cybersecurity, medicine, data science and neuroscience.

4. Brief Description of the Steps You Will Use to Solve this Challenge

a. High-level overview of your proposed solution for *(i) Use NISQ to distinguish data with known higher-order correlations from control data*:

We propose a hybrid classical–quantum approach that uses convolutional neural networks (CNNs) for initial spike feature extraction and quantum graph neural networks (QGNNs) to capture higher-order correlations within spike train data. The goal is to use near-term quantum devices to distinguish structured neural activity from randomized control datasets. Our strategy builds on the classical implementation of the CNN in Brand, D., Petruccione, F., 2024[1] to leverage its performance as it links to the QGNN in the Quantum Machine Learning (QML) pipeline.

b. Technical approach, including how you will utilize quantum computing feasibility and advantage over classical methods

The pipeline begins by importing neural data from the NWB files from DANDI using the Python library *pynwb,* followed by classical preprocessing steps such as spike alignment, waveform normalization, and segmentation. We then use CNN to extract compact, expressive feature vectors from each spike waveform. These features serve two roles: they are used directly for classical GNN benchmarking, and they also act as node attributes in a spike similarity graph constructed using temporal proximity or waveform similarity metrics. For quantum processing, the graph and its node features are encoded into a quantum circuit using angle or amplitude encoding, depending on available qubits and circuit depth constraints. Entangling gates (such as CNOT and RZ) are applied based on the graph's adjacency matrix, effectively allowing message passing through quantum entanglement. A variational quantum circuit is used per node, and the model is trained in a hybrid loop with a classical optimizer. This process allows the QGNN to identify higher-order patterns that may be invisible to classical models. The solution is NISQ-feasible, operating on qubits with shallow circuits, and prioritizes interpretability, modularity, and classical-quantum efficiency balance. A Quantum Error Correction (QEC) layer will also be applied at multiple stages and likely within a threshold to minimize error propagation in the pipeline. We are considering Pennylane, D-Wave and DANDI or Neurosift API.

c. Projected industry impact

By enabling richer pattern detection through quantum-enhanced graph reasoning, the model could improve early detection of neurological disorders, optimize closed-loop stimulation systems, support the development of adaptive neuro-prosthetics and aid in stroke recovery. Beyond healthcare, this work demonstrates a viable and scalable path to near-term quantum advantage in neuroscience, setting a precedent for hybrid AI–quantum systems across life sciences and complex systems modeling.

[1] Brand, D., Petruccione, F. A quantum leaky integrate-and-fire spiking neuron and network. npj Quantum Inf 10, 125 (2024). https://doi.org/10.1038/s41534-024-00921-x