Quantum Machine Learning for High Energy Physics

Quantum Contrastive Learning

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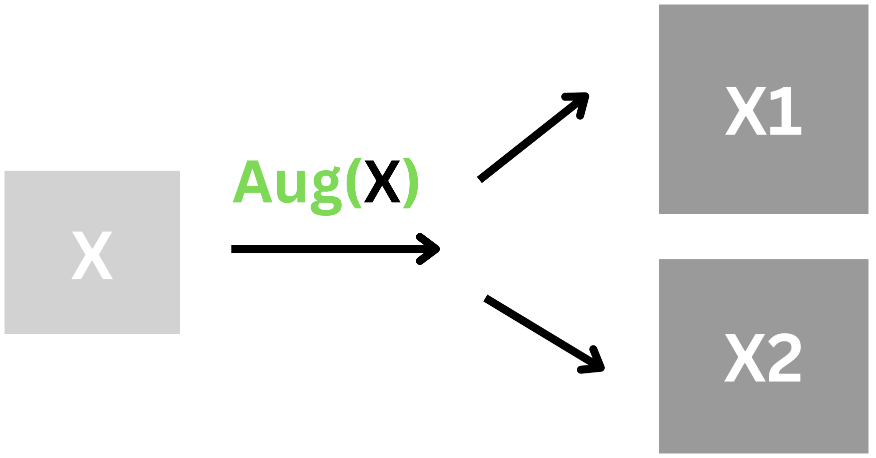
Mid-term Evaluation

Contrastive Learning Framework

Data Augmentation Module - Aug()



Augmented views from same sample - positive pair
Augmented views from different samples - negative pair

Encoder network - Enc()

Z1, Z2 = Representations for a positive pair

Objective

Learn encoder such that it minimizes distance between positive pairs and maximizes distance between negative pairs

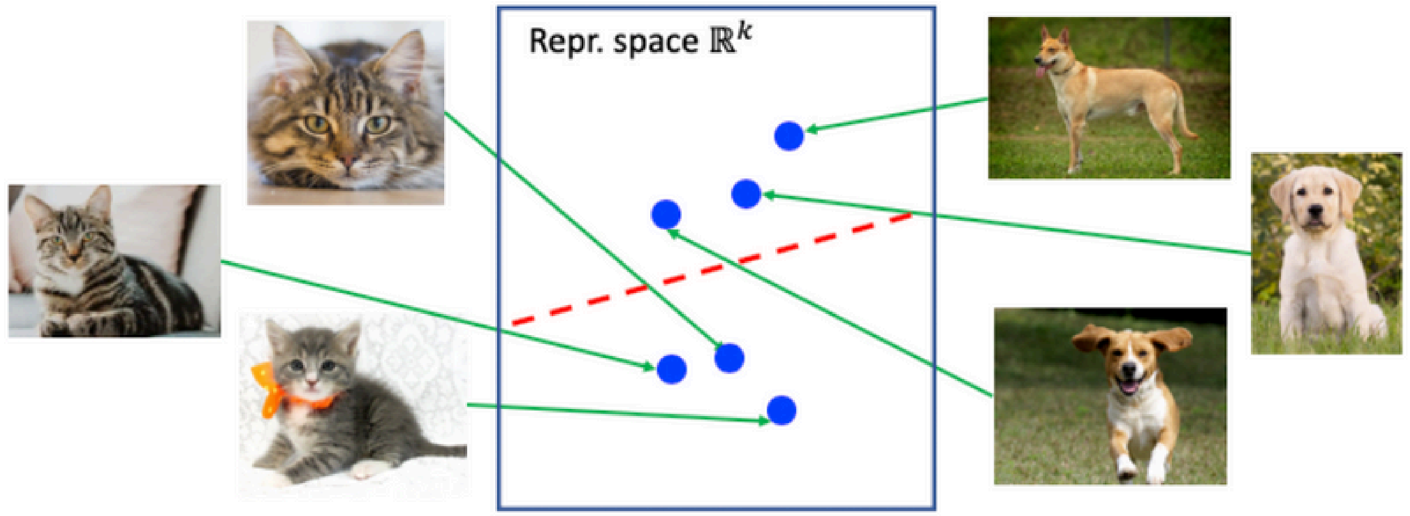
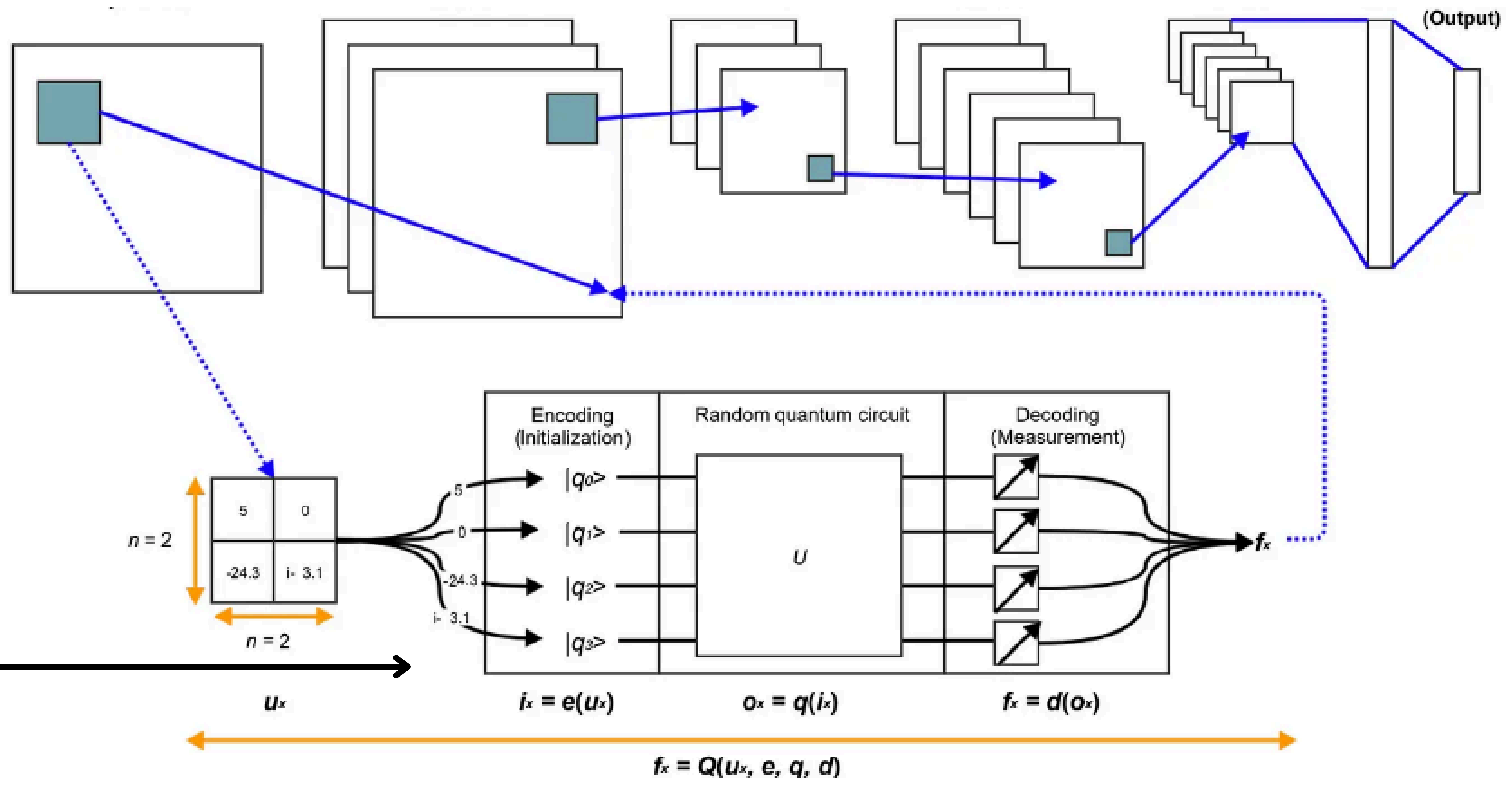


Image credits - Stanford AI Lab blog

Data Augmentation

- Random Horizontal flips
- Random Vertical flips
- Random Rotations
- Z-score Normalization

Encoder



Data-Reuploading circuits (DRC)

HYBRID

- Quantum Convolution layers followed by a classical Linear layer
- Output - N-dimensional vector

FULLY-QUANTUM

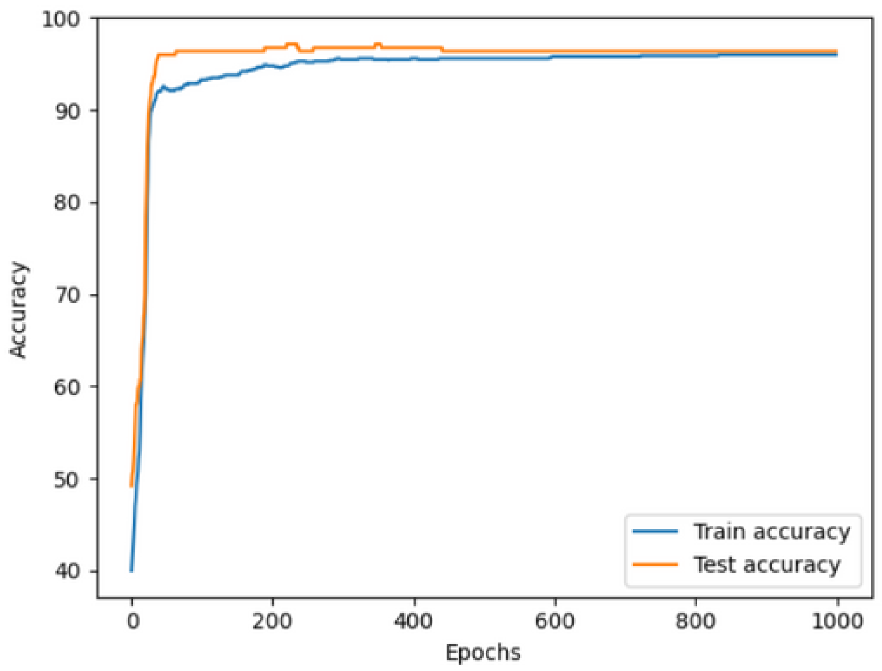
- Quantum Convolution layers followed by a parameterised quantum circuit
- Output - 2^n dimensional quantum state vector

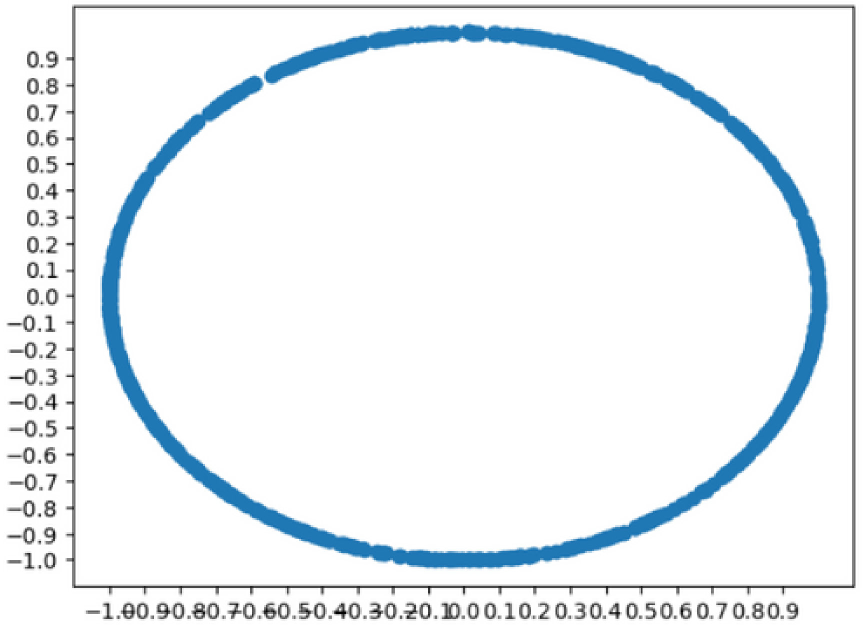
Image credits - https://arxiv.org/pdf/1904.04767

Performance Evaluation - Classification using trained representations

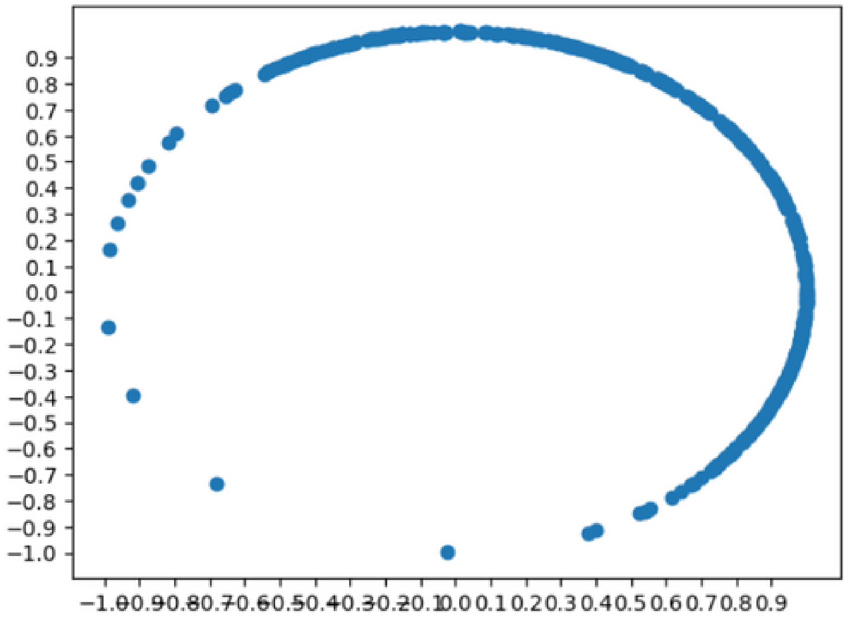
Results - MNIST 0s and 8s

Hybrid

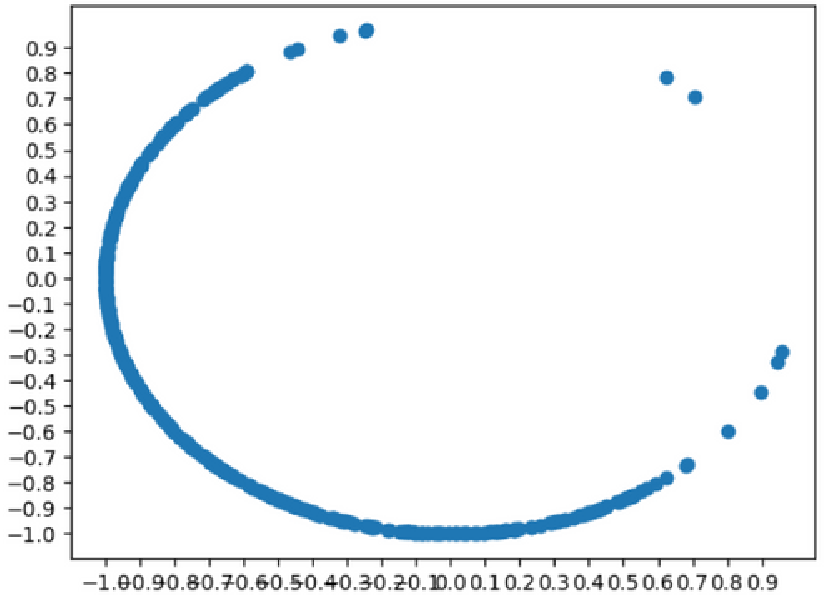




Combined

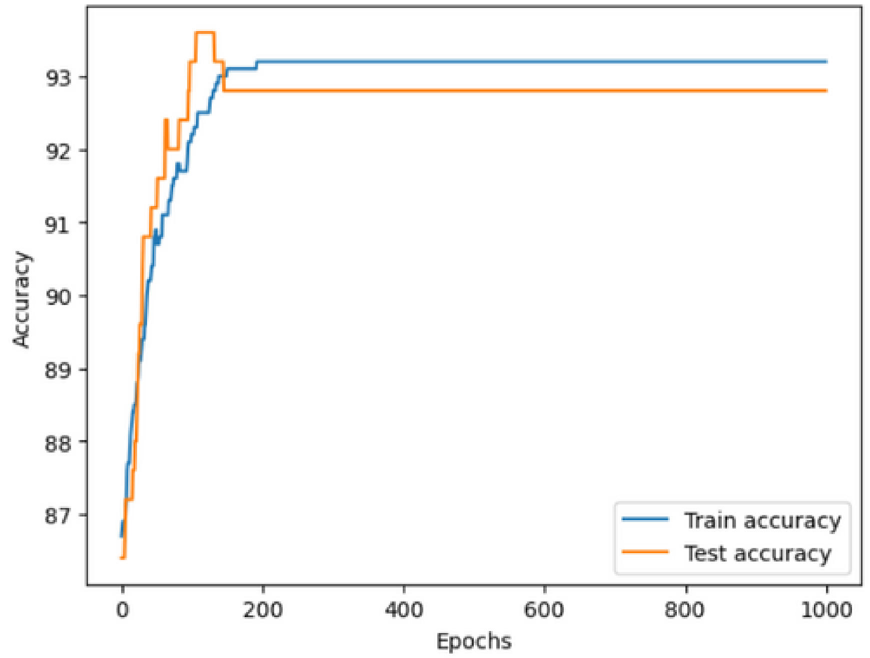


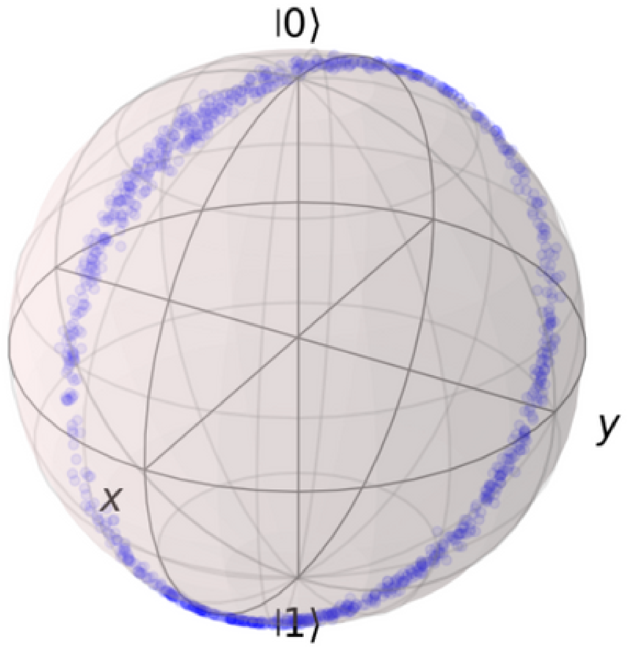
0s



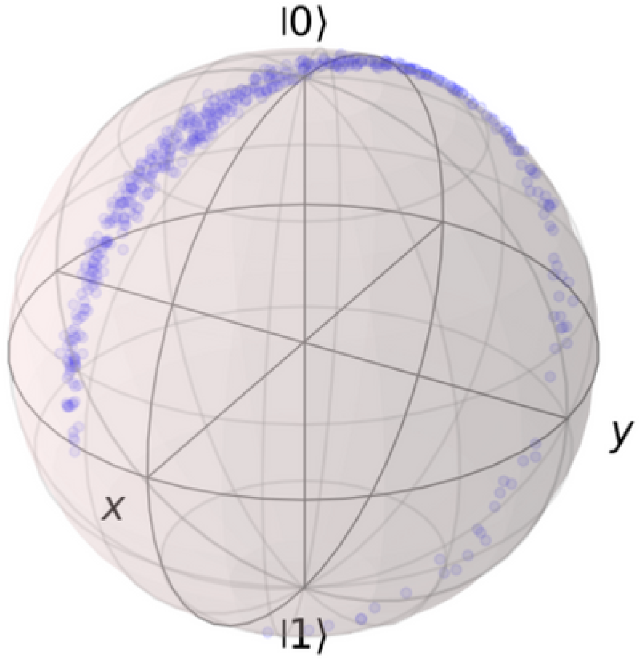
8s

Fully - Quantum

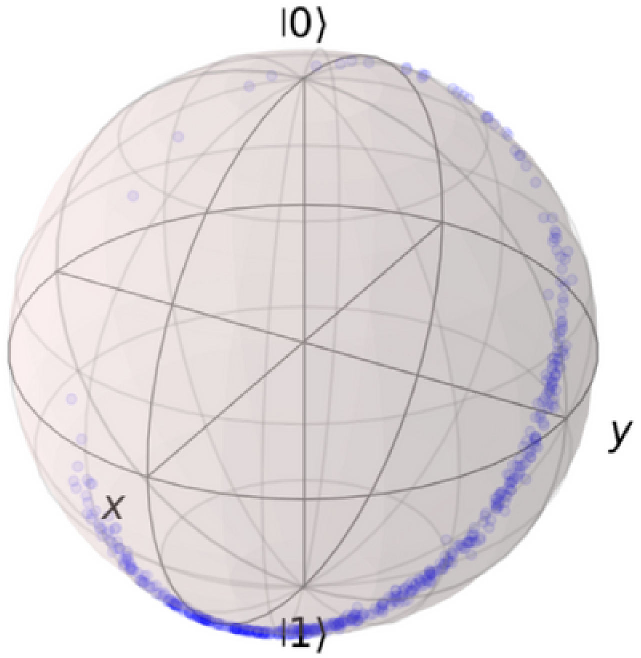




Combined



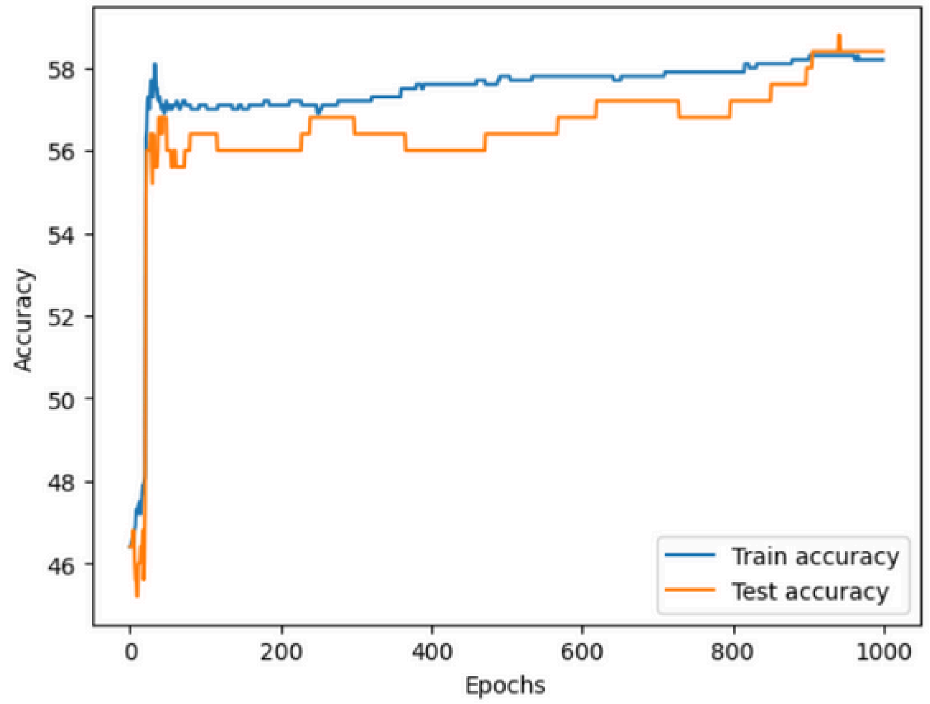
0s

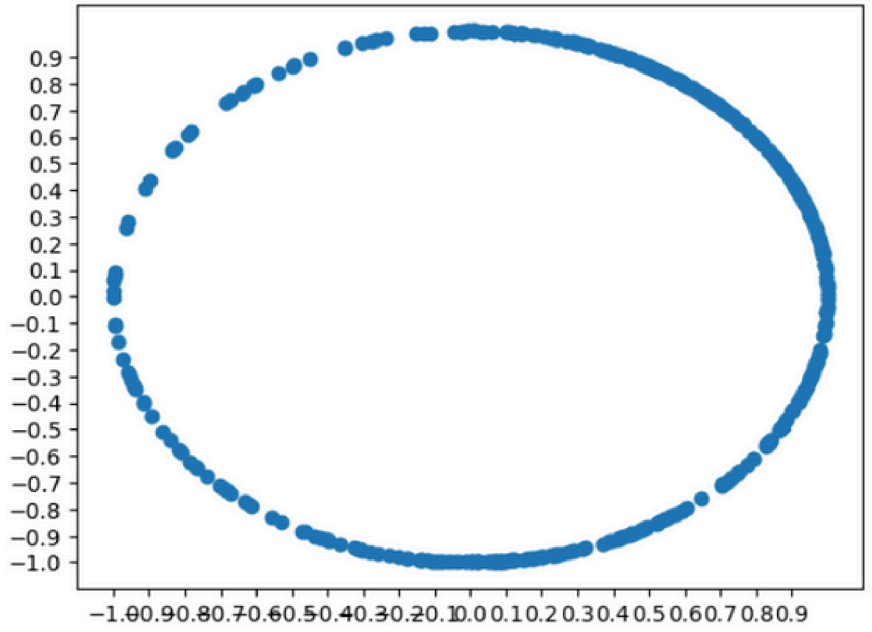


8s

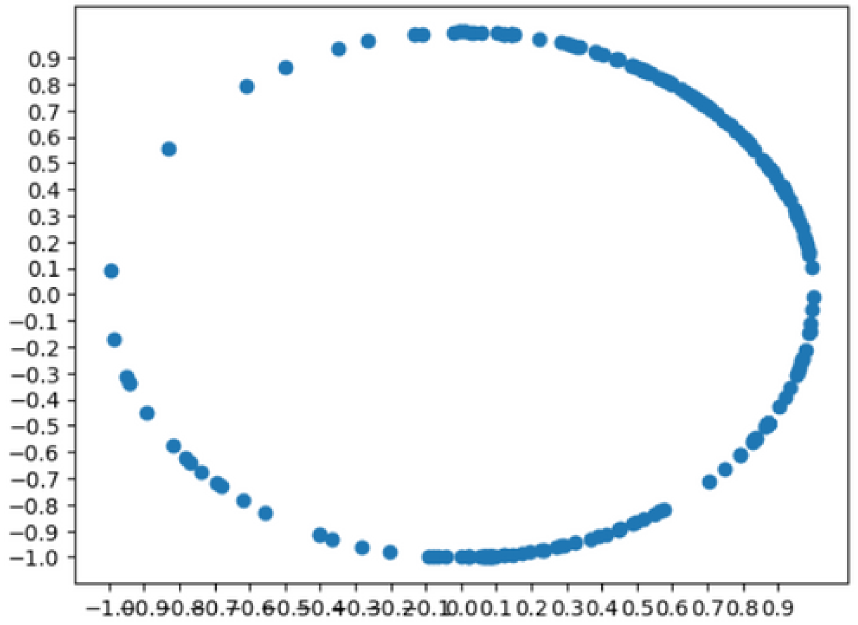
Results - Quarks and Gluon images (Tracks)

Hybrid

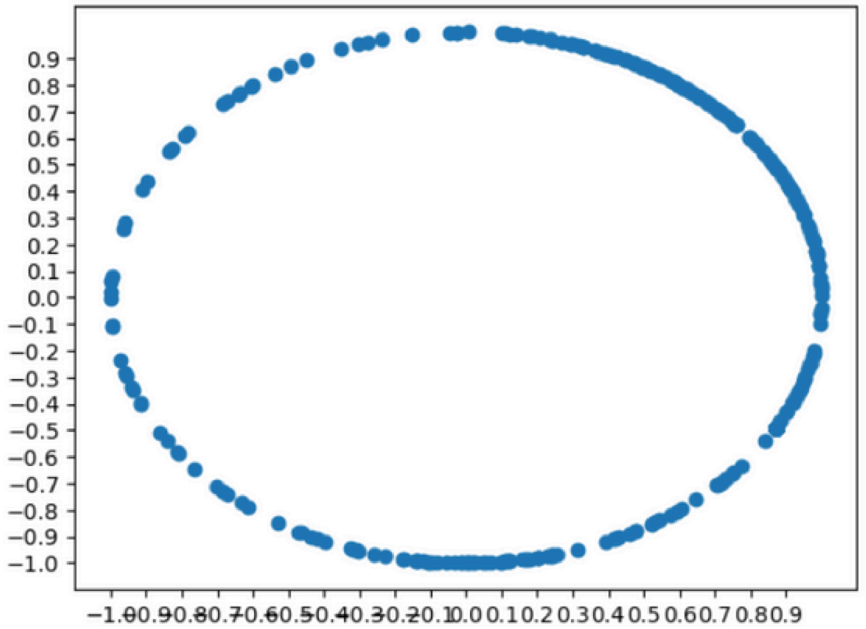




Combined

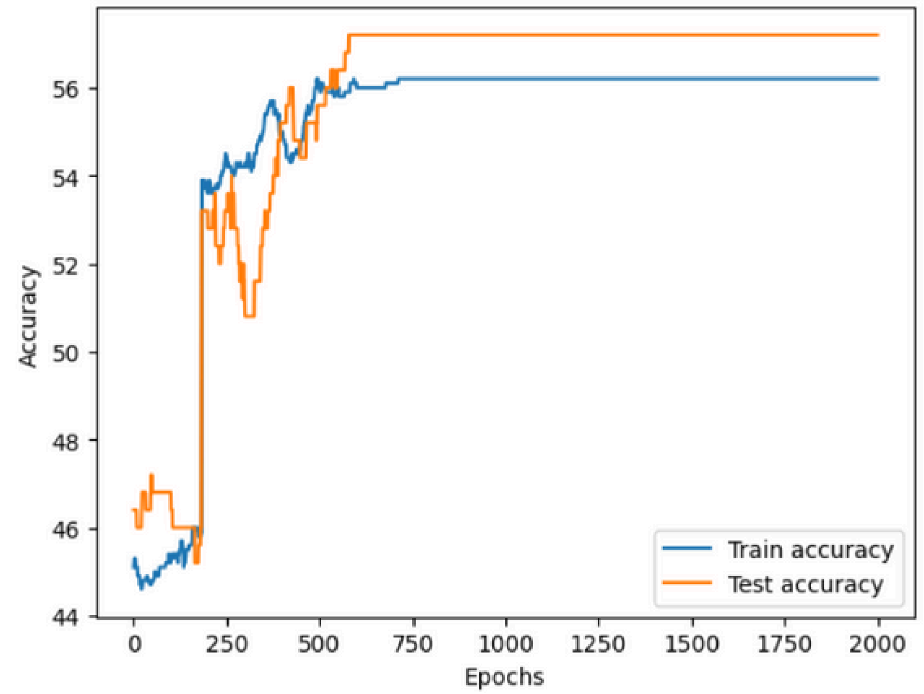


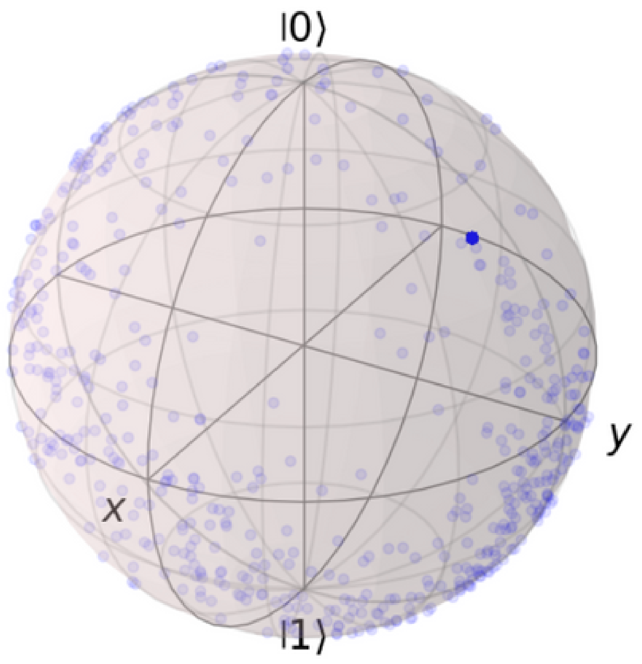
Quark



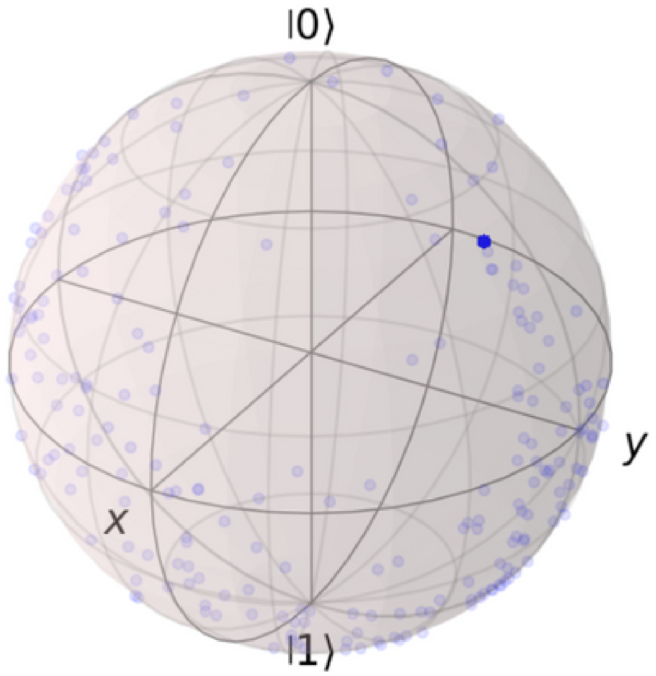
Gluon

Fully - Quantum

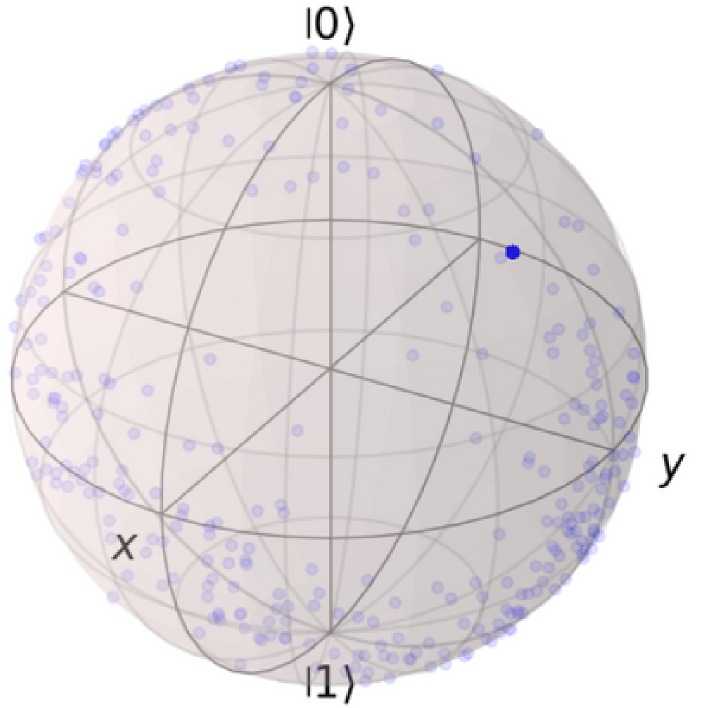




Combined

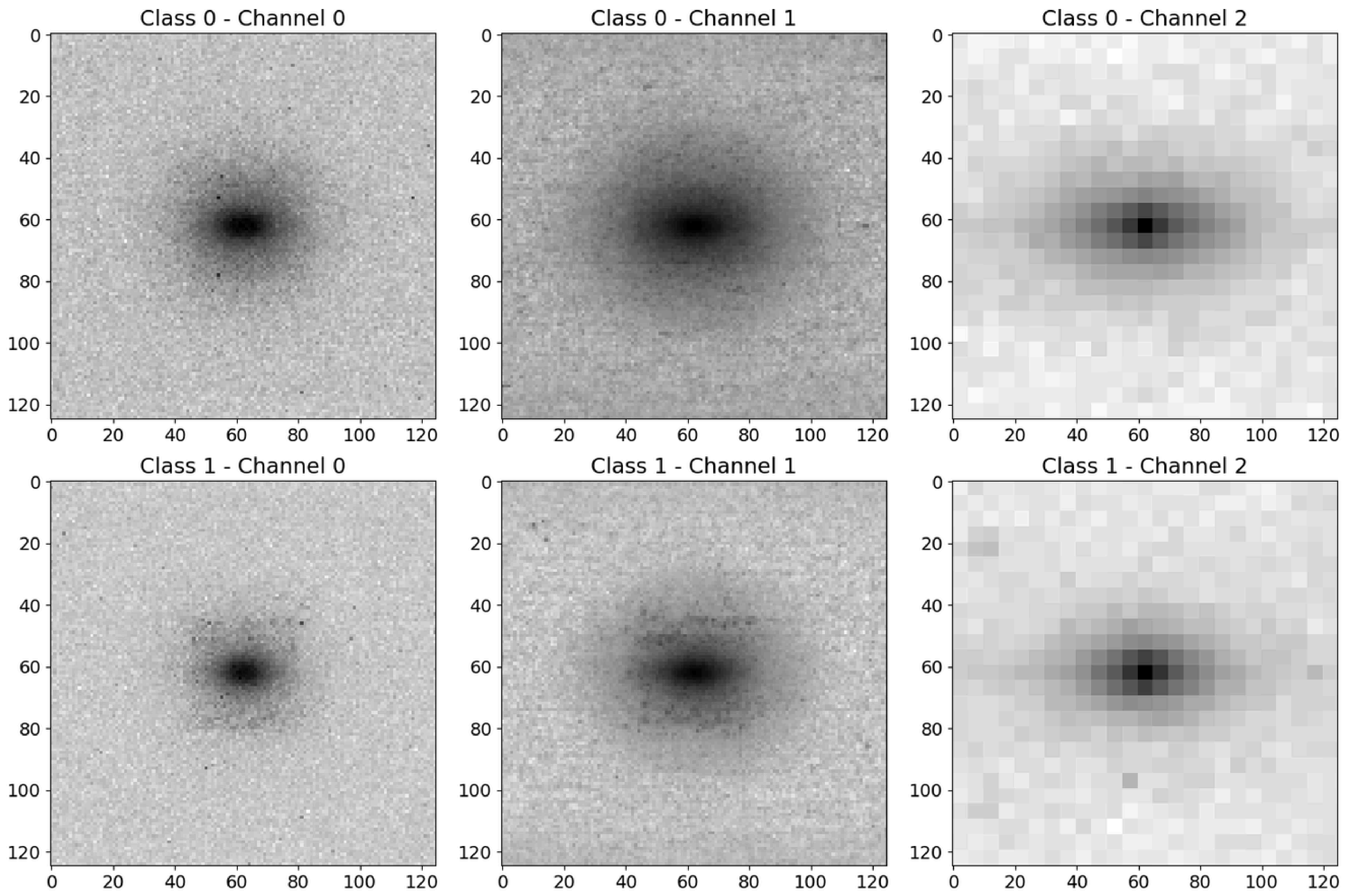


Quark



Gluon

Average of quark-gluon images for different channels



Tracks ECAL HCAL

Challenges

- Capturing correlations between channels
- Different resolution for each channel

Next steps...

Quantum Graph Contrastive Learning

- Convert input samples into graphs
- Perform graph augmentations
- Use Graph NN as an encoder
- Use ideas from **causal inference** to capture correlations