# Automated Medical Image Diagnostics using QML

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M.Tech Quantum Technologies

Problem Statement

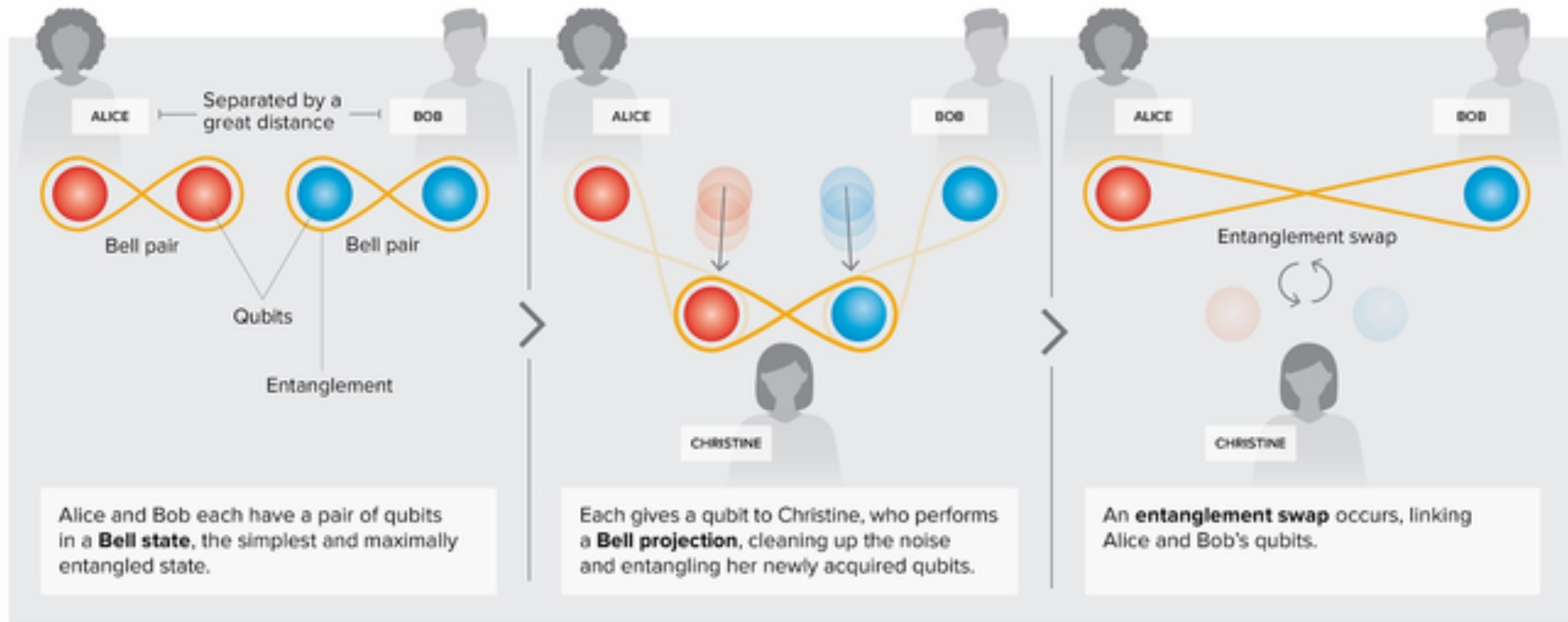Our mission is to delve into the unique convergence of quantum computing and image analysis.

Specifically, we aim to implement a model classifying face image data set to predict disorders (i.e.,Parkinson's, Autism, etc), And to unravel the mysteries of QCNN architecture and its application in classifying images.
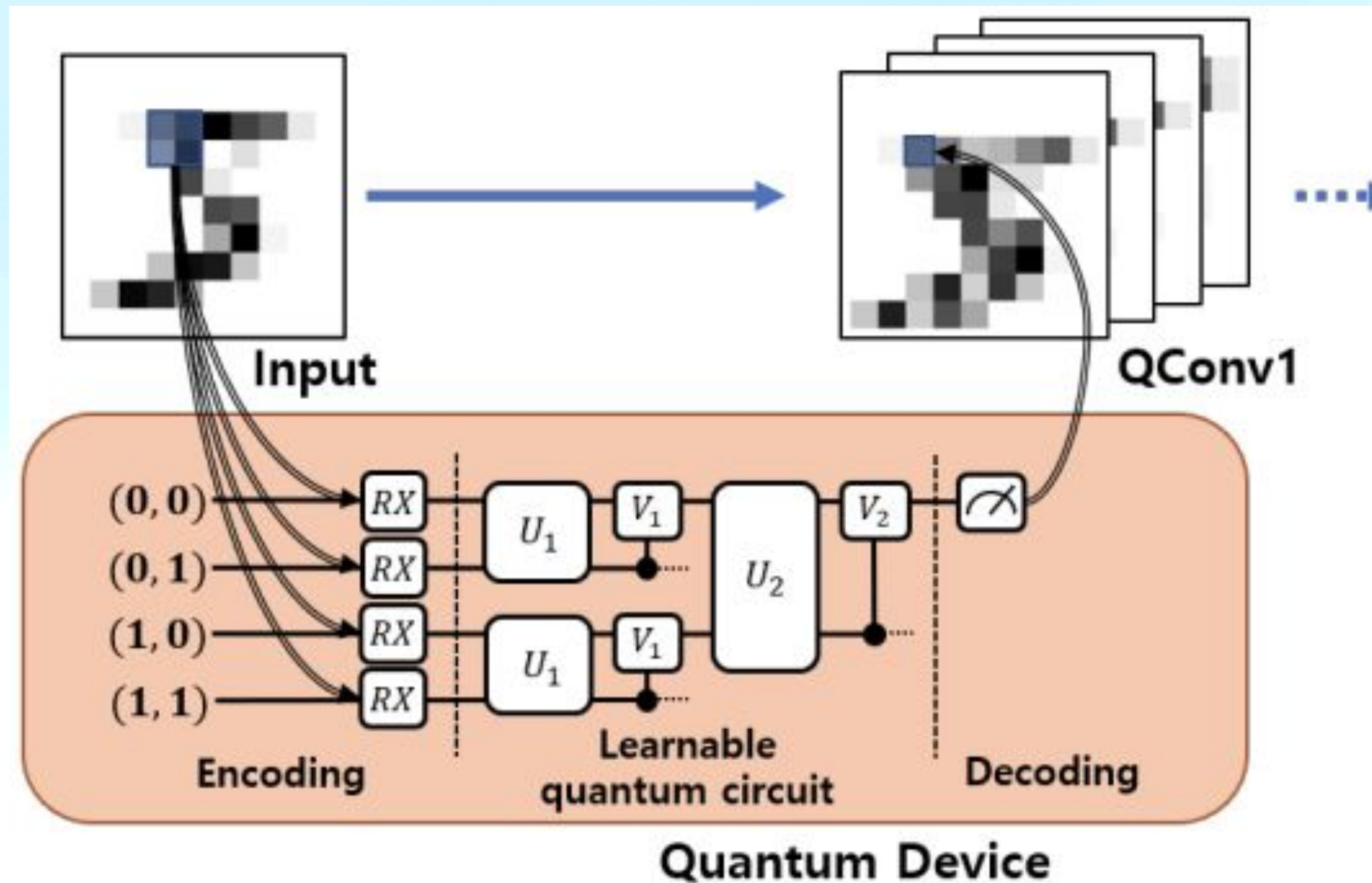
Conditions for Quantum Computation
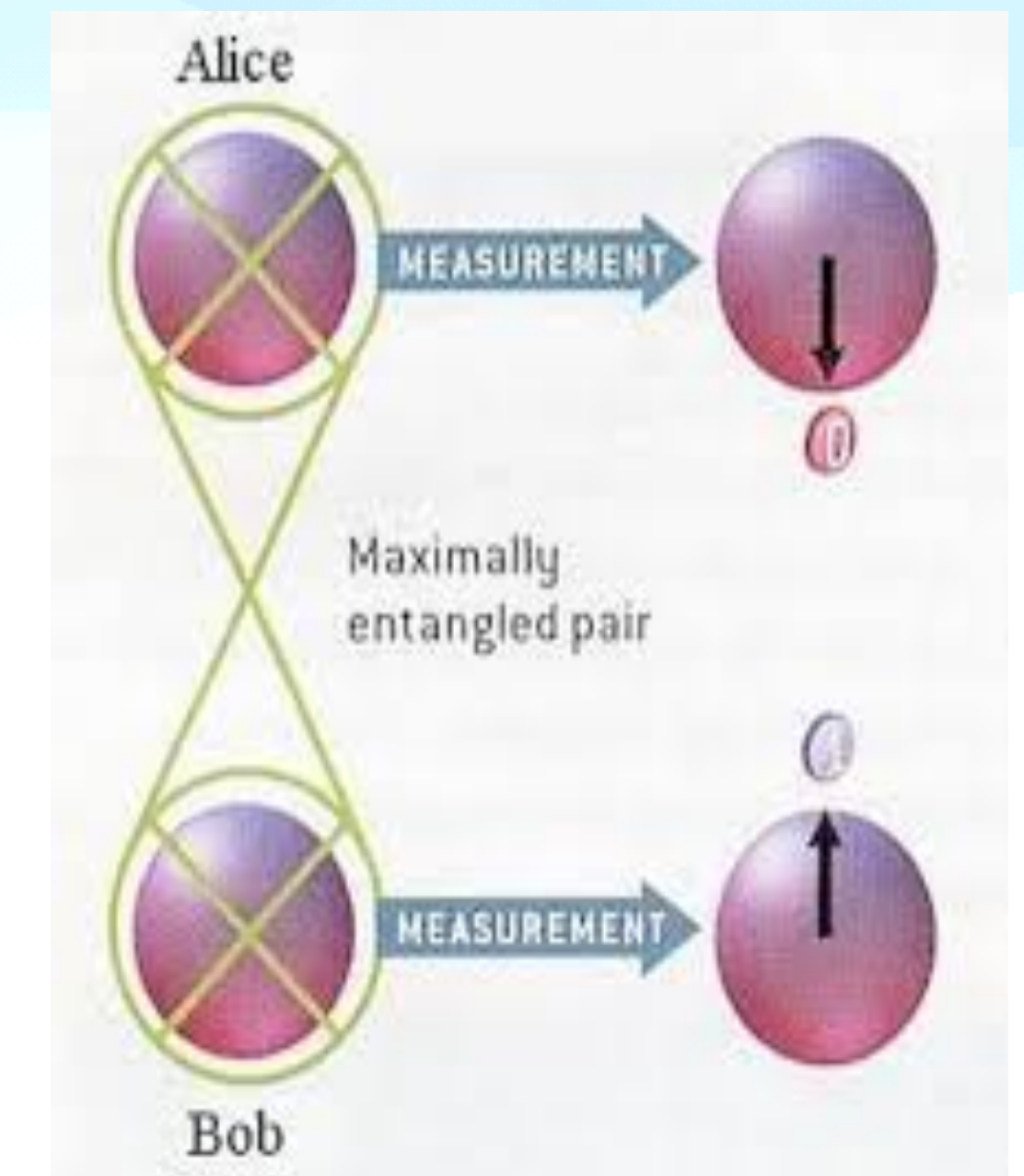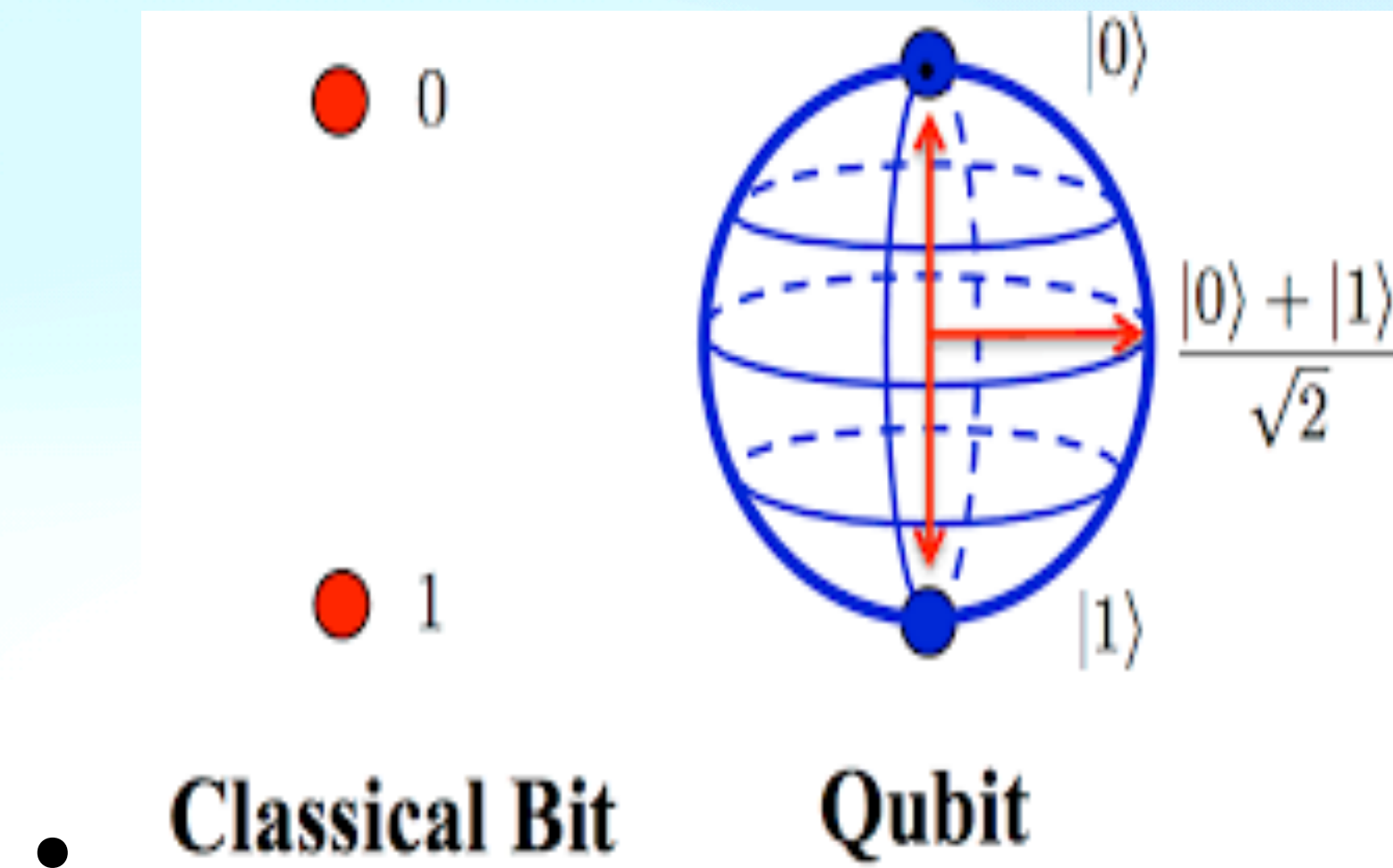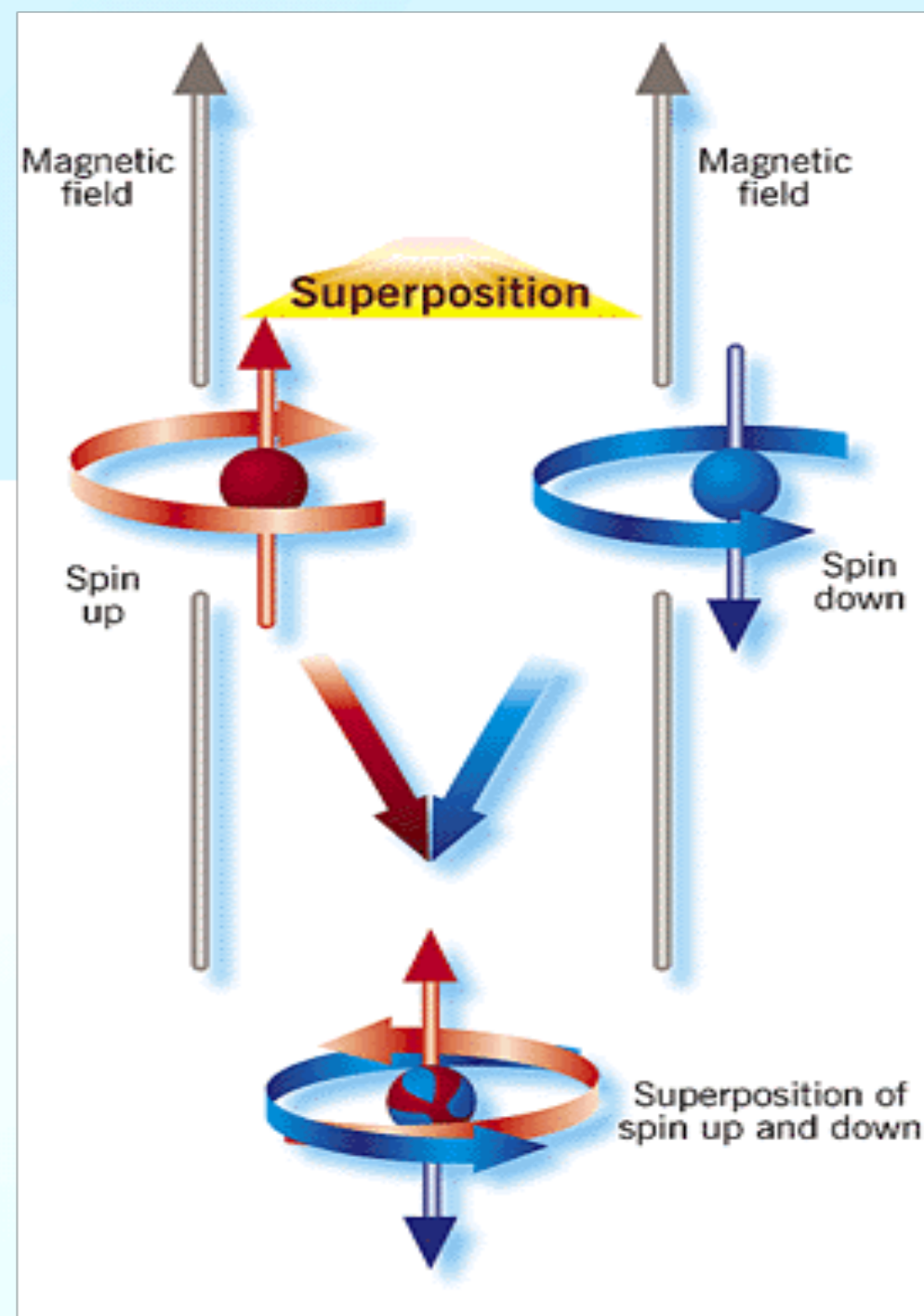
QUANTUM ENTANGLEMENT
SWAPPING

Building a quantum information network will rely on entangling qubits across great distances

ALICE — Separated by a great distance — BOB

Bell pair Bell pair

Qubits

Entanglement

Alice and Bob each have a pair of qubits in a **Bell state**, the simplest and maximally entangled state.

CHRISTINE

Each gives a qubit to Christine, who performs a **Bell projection**, cleaning up the noise and entangling her newly acquired qubits.

Entanglement swap

CHRISTINE

An **entanglement swap** occurs, linking Alice and Bob's qubits.

QCNN Architecture

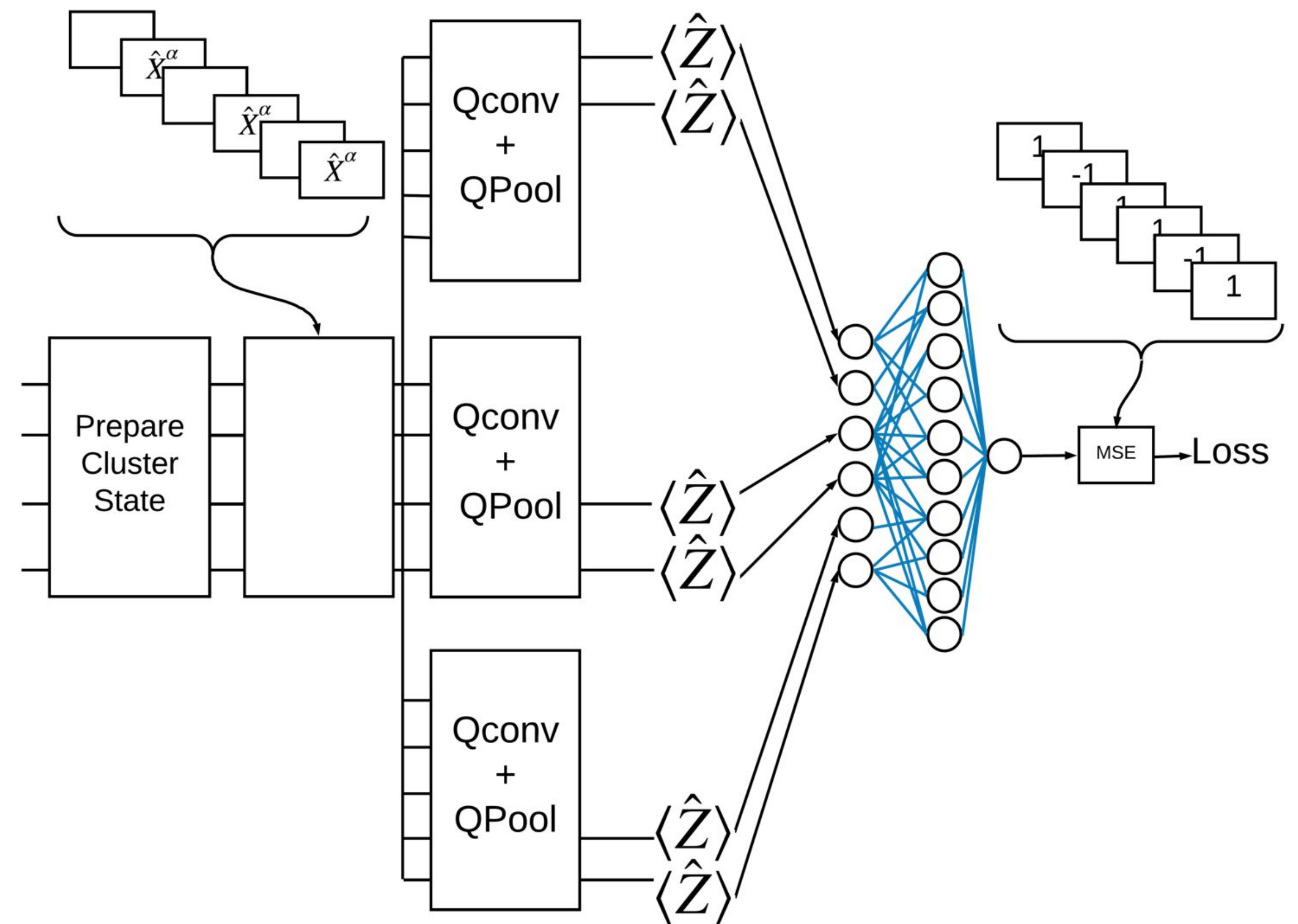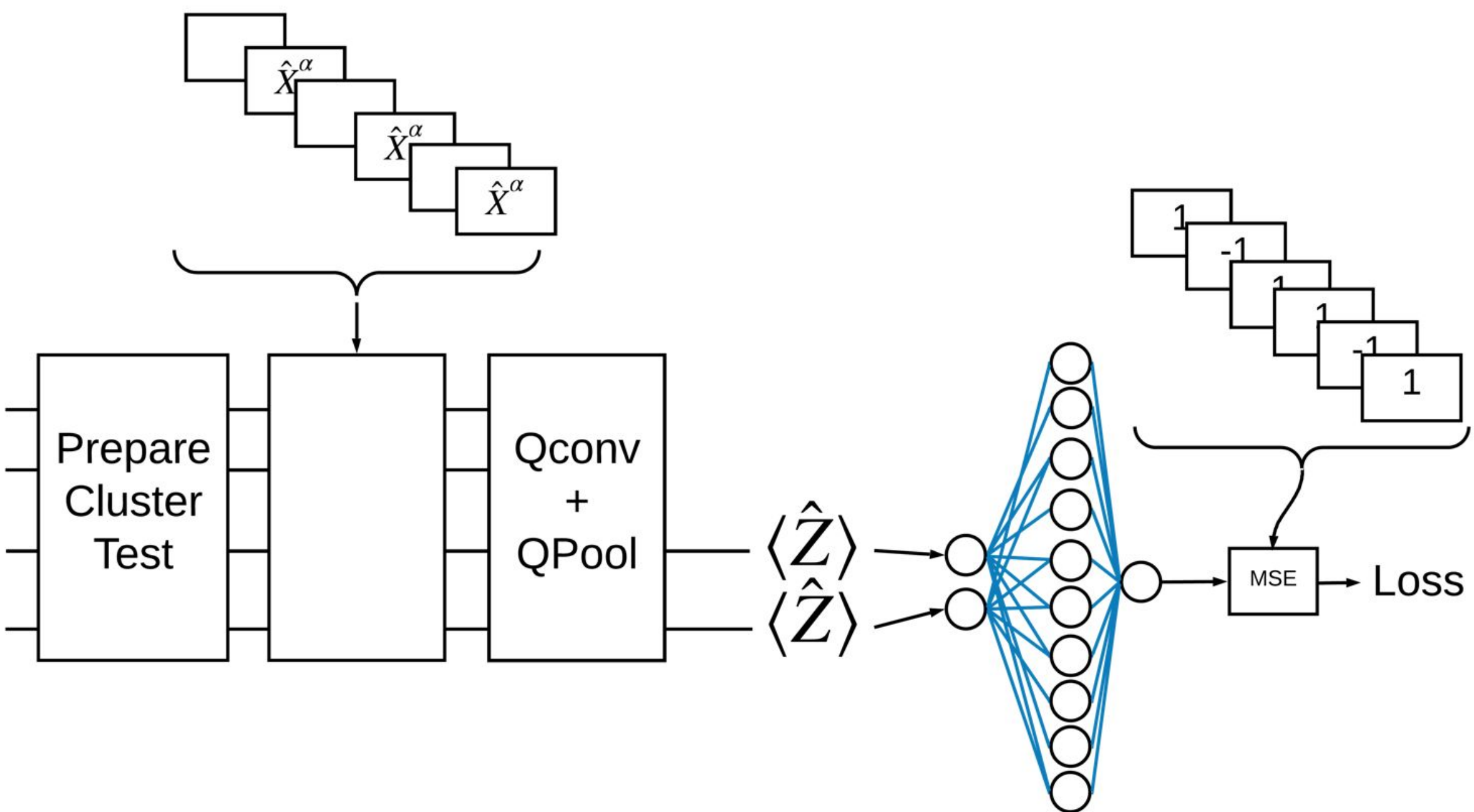**Understanding CNN with Quantum circuits, Image credits : Pennylane**

Overview

Libraries used for code

Preparation of Dataset's
Medical image dataset of Autism

We have collected medical image dataset which represents patient with and without Autism.

Dataset from Kaggle

Design and Implementation

- Quantum circuit as a convolution kernel
- Quantum pre-processing of the dataset
- Hybrid quantum-classical model

Training the dataset

```python
# Quantum pre-processing of train images
q_train_images = []
print("Quantum pre-processing of train images:")
for idx, img in enumerate(train_images):
    print("{}/{}        ".format(idx + 1, len(train_images)), end="\r")
    q_train_images.append(quanv(img))
q_train_images = np.asarray(q_train_images)

# Quantum pre-processing of test images
q_test_images = []
print("\nQuantum pre-processing of test images:")
for idx, img in enumerate(test_images):
    print("{}/{}        ".format(idx + 1, len(test_images)), end="\r")
    q_test_images.append(quanv(img))
q_test_images = np.asarray(q_test_images)

# Save pre-processed images
SAVE_PATH = "your_save_path/"
if not os.path.exists(SAVE_PATH):
    os.makedirs(SAVE_PATH)

np.save(SAVE_PATH + "q_train_images.npy", q_train_images)
np.save(SAVE_PATH + "q_test_images.npy", q_test_images)
```
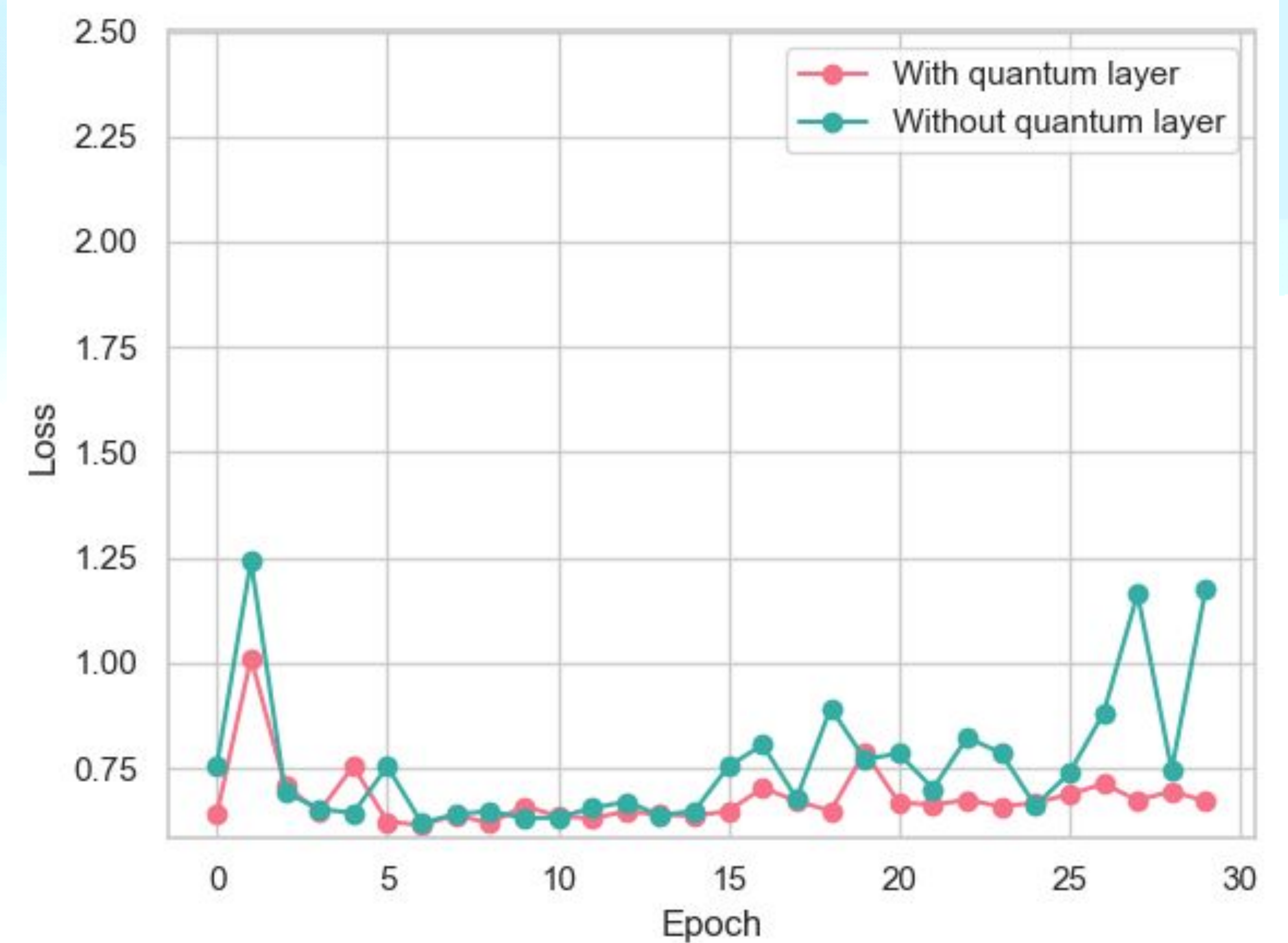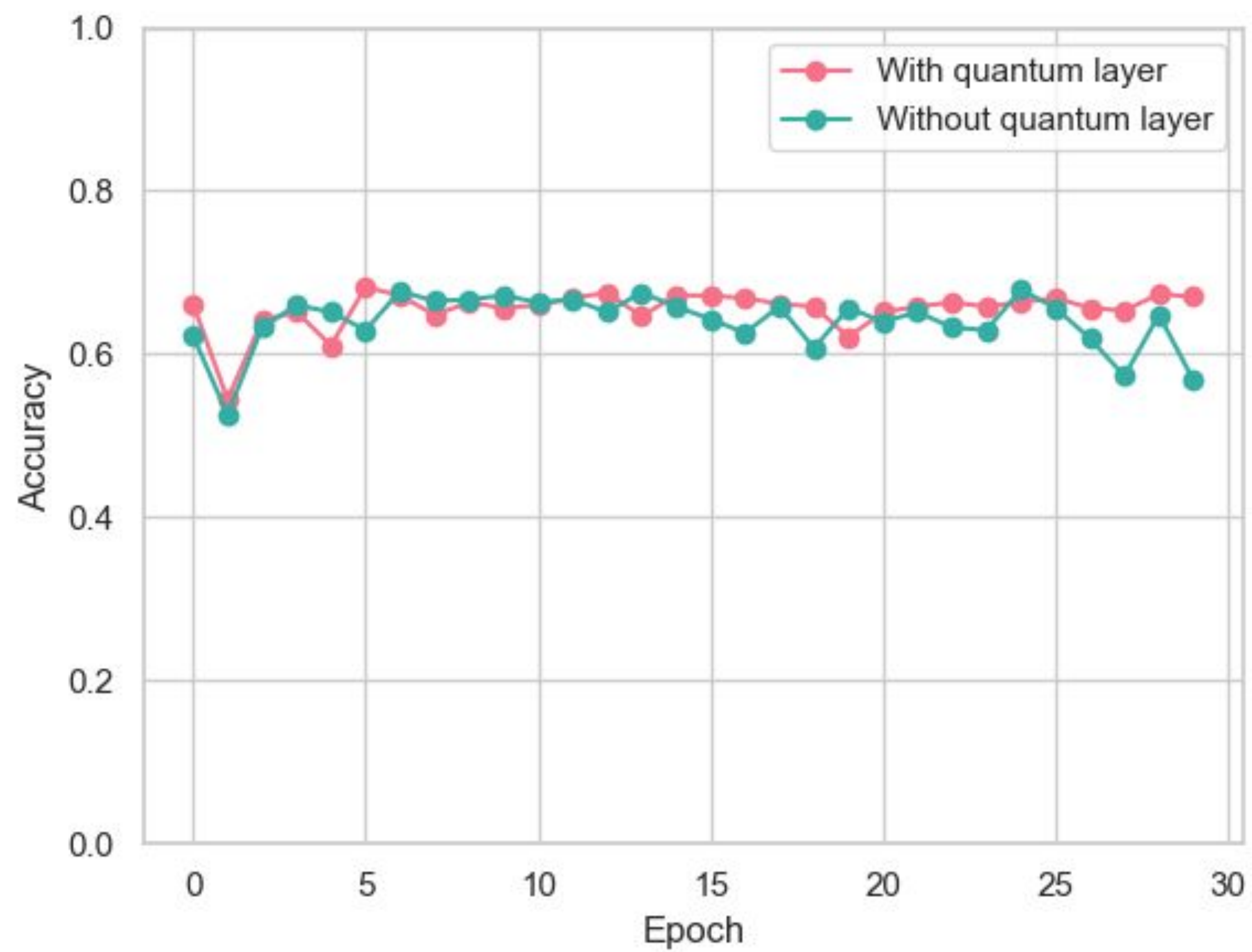
File display

- 80% datasets were used for training and rest were used for testing.

Result and Observation

Reference's

- [1] Andrea Mari, Thomas R. Bromley, Josh Izaac, Maria Schuld, and Nathan Killoran. Transfer learning in hybrid classical-quantum neural networks. arXiv:1912.08278 (2019).

- [2] Maxwell Henderson, Samriddhi Shakya, Shashindra Pradhan and Tristan Cook.Quantum Convolutional Neural Networks: Powering Image Recognition with Quantum Circuits. Sub- mitted on 9 Apr 2019. arXiv:1904.04767

- [3] Rajat Raina, Alexis Battle, Honglak Lee, Benjamin Packer, and Andrew Y Ng. Self-taught learning: transfer learning from unlabeled data. Proceedings of the 24th International Con- ference on Machine Learning*, 759–766 (2007).

- [4] Ville Bergholm, Josh Izaac, Maria Schuld, Christian Gogolin, Carsten Blank, Keri McK- iernan, and Nathan Killoran. PennyLane: Automatic differentiation of hybrid quantum- classical computations. arXiv:1811.04968 (2018).
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