

Hybrid Quantum-Classical Classifier

A Quantum Variational Approach to Feature-Aware Medical Diagnosis

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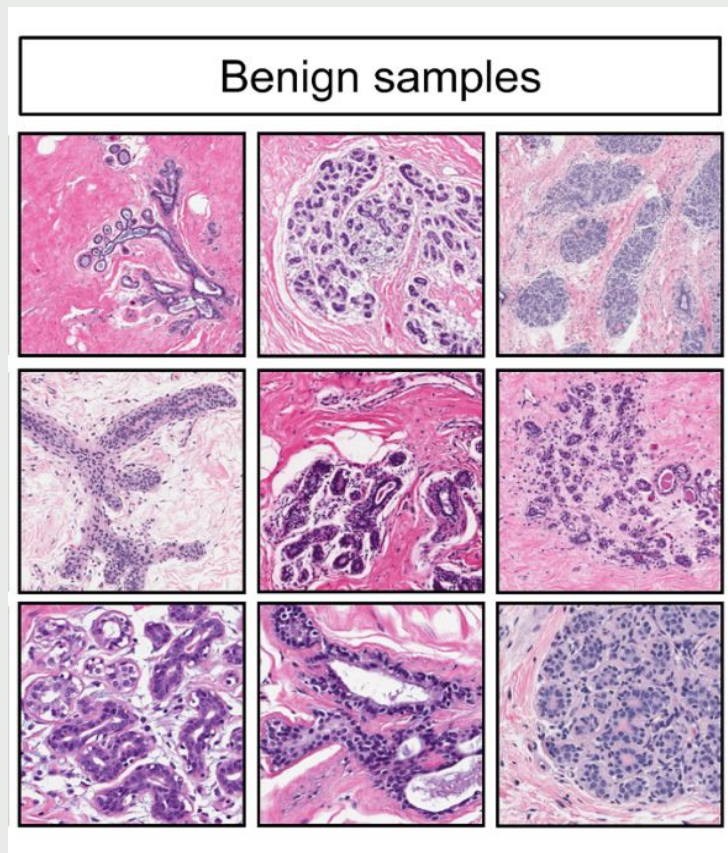
Introduction

We developed and compared classical, quantum, and hybrid models for breast cancer classification, using quantum circuits to explore potential gains from entanglement and quantum feature spaces in medical diagnostics.

Background

The Breast Cancer Diagnostic dataset contains 30 numerical features derived from cell nuclei images, used to classify tumors as malignant or benign.

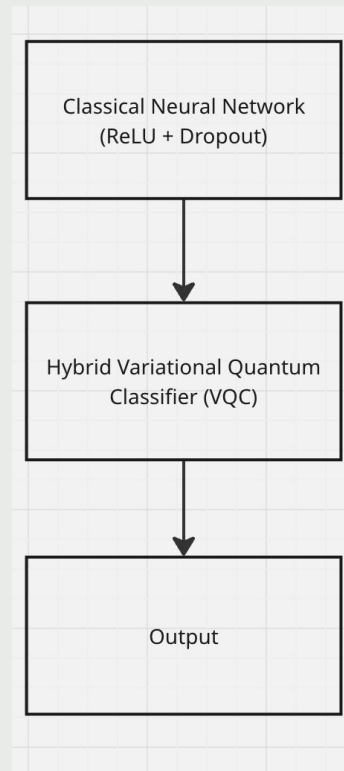
We built our models using PyTorch for neural network training, PennyLane for quantum circuit simulation and integration, scikit-learn for preprocessing and data handling, and Matplotlib for result visualization.



Credit: UCI ML Databases

Overall Architecture

1. Classical ML:
 - Pure NN with ReLU + dropout
2. Quantum ML:
 - Hybrid VQC
3. Hybrid
 - **Classical NN → Quantum layer → Output**



Overall Model Architecture

The Quantum Circuit

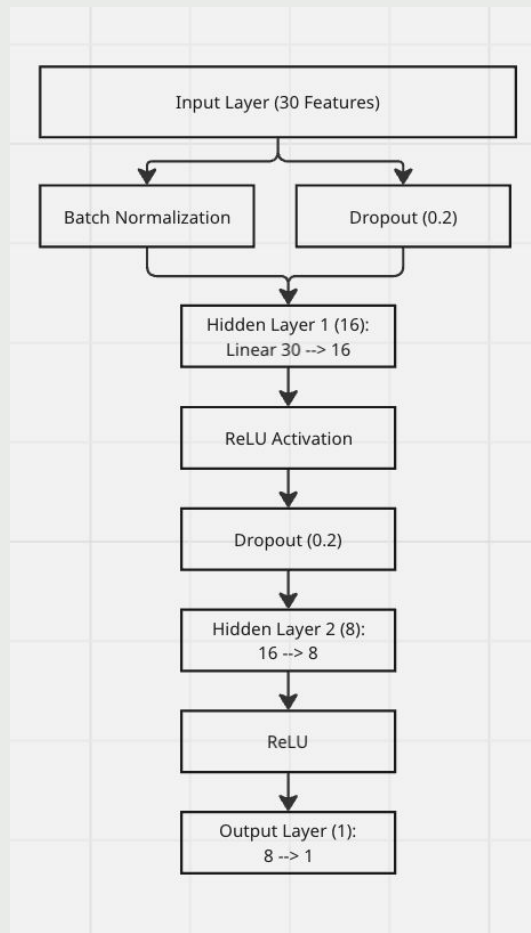
1. AngleEmbedding
 - Encodes data as rotations around Y axis
2. StronglyEntanglingLayers
 - Learn feature interactions
3. QNode Output
 - $\langle Z_0 \rangle, \dots, \langle Z_{n-1} \rangle$ — expectation values

```
# ===== QUANTUM CONFIGURATION =====  
n_qubits = 4  
dev = qml.device("default.qubit", wires=n_qubits)  
  
@qml.qnode(dev, interface="torch", diff_method="backprop")  
def quantum_circuit(inputs):  
    AngleEmbedding(inputs, wires=range(n_qubits), rotation='Y')  
    StronglyEntanglingLayers(weights=torch.ones((1, n_qubits, 3)), wires=range(n_qubits))  
    return [qml.expval(qml.PauliZ(i)) for i in range(n_qubits)]
```

The Classical Model

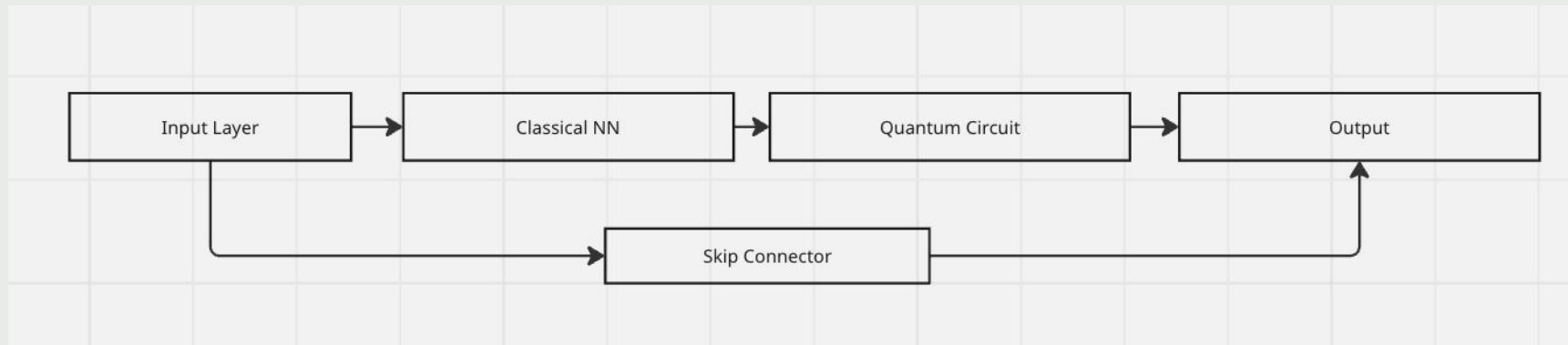
1. Feedforward MLP with:

- BatchNorm1d(30)
- Linear layers: $30 \rightarrow 16 \rightarrow 8 \rightarrow 1$
- Activation: ReLU
- Regularization: Dropout



Quantum-Classical Hybrid: Best of Both Worlds

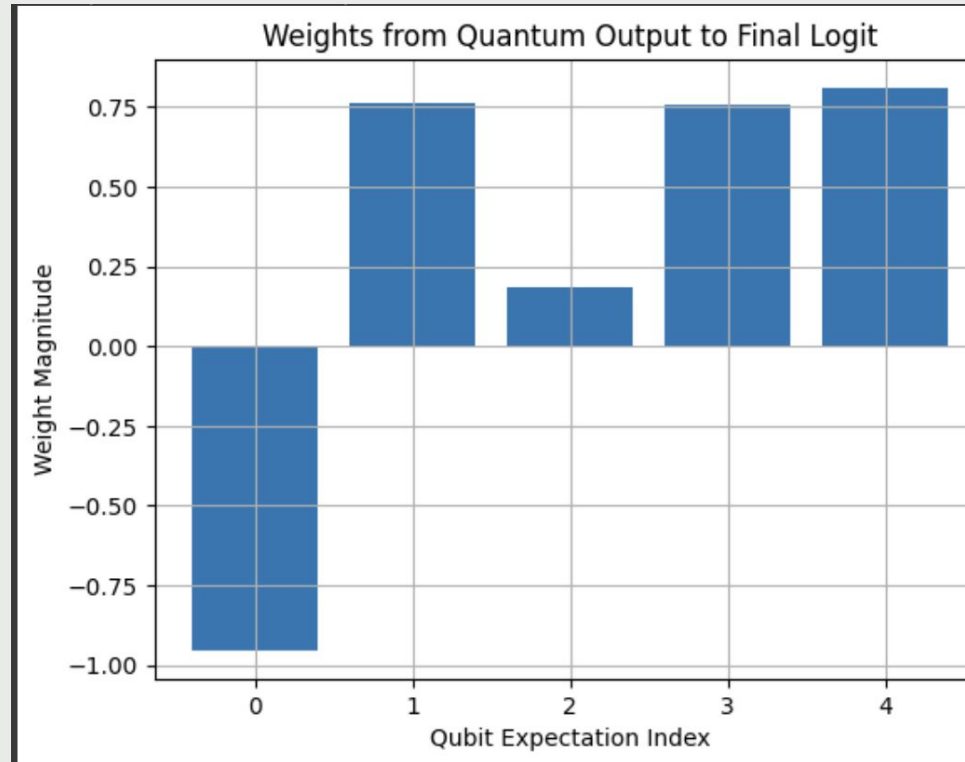
1. Classical Feature Extractor: $30 \rightarrow 16 \rightarrow n_qubits$
2. Quantum Circuit: Acts on compressed features
3. Skip Connection: Helps preserve classical signal



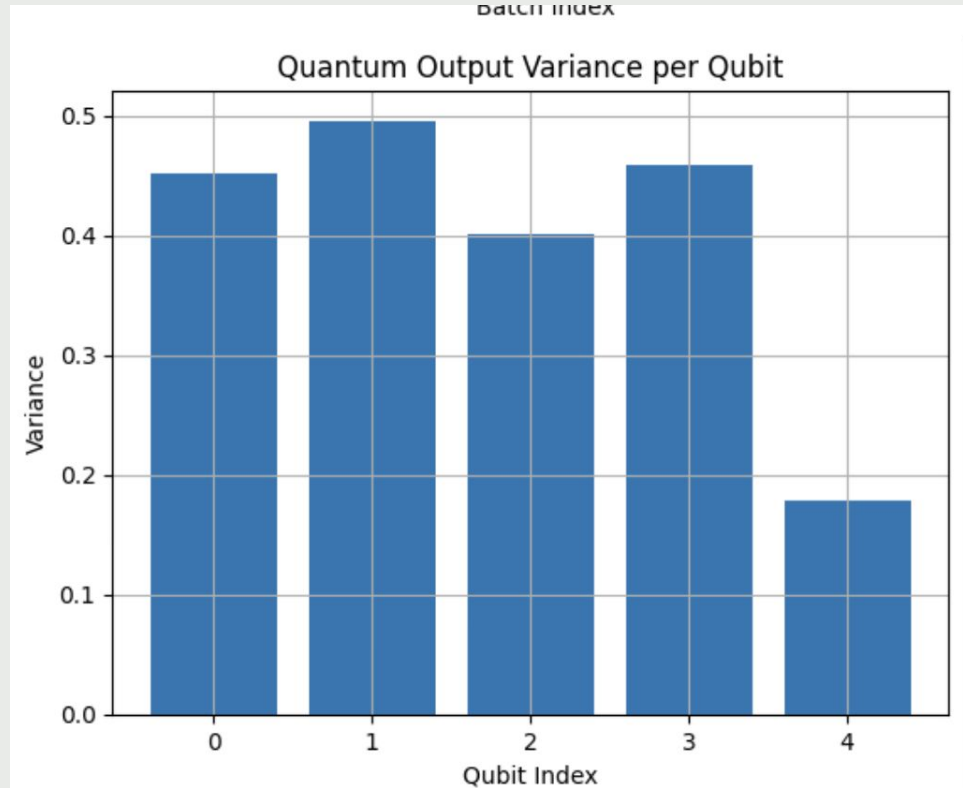
Training

1. Loss Function: BCEWithLogitsLoss()
2. Optimizer: Adam (lr=0.003, weight decay)
3. Scheduler: StepLR
4. 60 epochs, batch size = 32
 - a. Validation every epoch

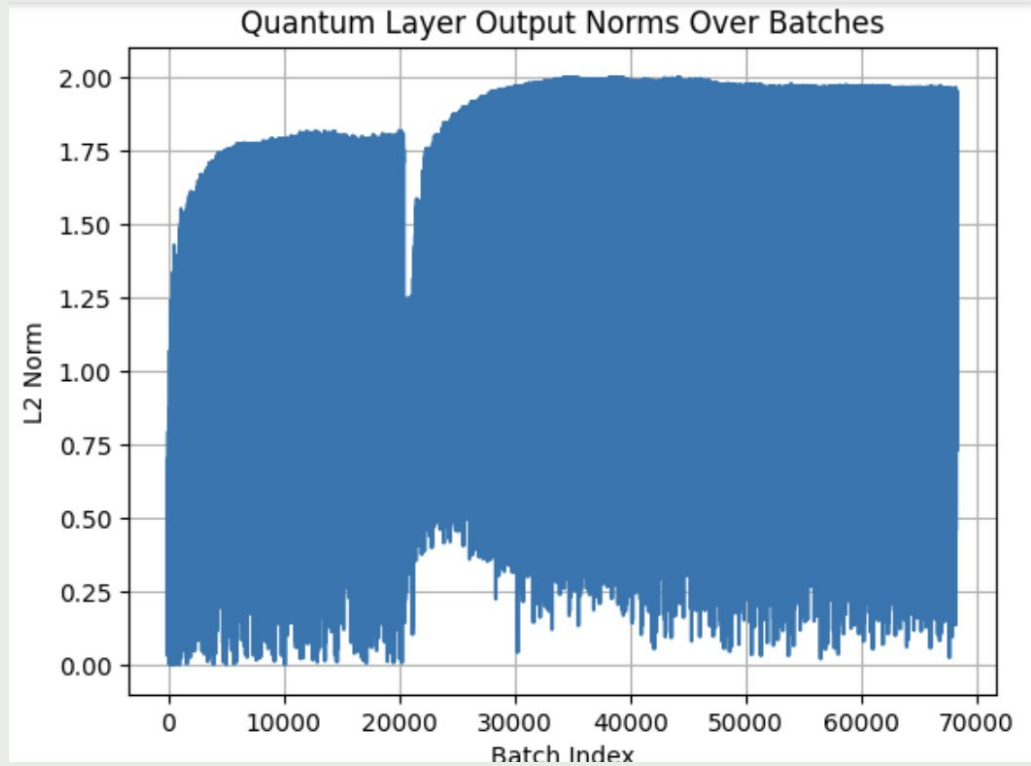
Results



Results



Results



Key Takeaways

1. Hybrid Superiority

- a. The Full Hybrid model outperforms both pure classical and pure quantum models by 1.76% (absolute improvement).

2. Quantum Alone $\neq$ Advantage

- a. Raw quantum circuits need classical preprocessing for real-world tasks.
- b. Hybrid architectures mitigate quantum noise/limitations.

3. Practical Impact

- a. 1.76% improvement in medical diagnostics could translate to:
- b. Fewer false negatives in cancer detection.
- c. More reliable automated screening tools