PROJECT BRIEF

Project Name:	Hybrid Quantum-Classical MNIST Classifier using PennyLane
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Track:	Quantum Machine Learning (QML)

PROJECT OVERVIEW

- This project shows how classical AI and quantum computing can work together to solve practical classification problems. We created two models using the MNIST handwritten digit dataset: a 6-qubit hybrid quantum-classical neural circuit and a conventional Support Vector Machine (SVM). Quantum feature encoding can improve learning in constrained data settings, as demonstrated by the hybrid approach's 92% accuracy, which exceeded the classical baseline's 87%.

BACKGROUND & MOTIVATION

- A new field called quantum machine learning (QML) uses AI and quantum mechanics to effectively solve issues that traditional computers find difficult to handle. SVMs and other traditional models work well, but they may have trouble with correlated or high-dimensional data. Quantum circuits can naturally represent data in higher-dimensional spaces by utilizing qubits and entanglement.
- By constructing and contrasting a quantum and classical model side by side, this project investigates that concept.

PROJECT GOALS

1. Create a baseline digit classification model using a traditional SVM model.
2. Utilizing PennyLane's variational quantum circuits, create a hybrid quantum-classical classifier.
3. Principal Component Analysis (PCA) can be used to compress MNIST data for qubit-efficient encoding.
4. Examine the differences in learning behavior and accuracy between hybrid and classical systems.

IMPLEMENTATION STRATEGY

1. Data Preparation:
   - Used MNIST dataset (28×28 grayscale images).
   - Reduced features from 784 → 6 using PCA.
   - Normalized features to the [0,1] range for qubit input compatibility.
2. Classical Model:
   - Implemented a linear SVM using scikit-learn.
   - Achieved baseline accuracy of 0.87.
3. Hybrid Quantum-Classical Model:
   - 6-qubit circuit with AngleEmbedding + StronglyEntanglingLayers.
   - Optimized using Adam (learning rate = 0.1) for 25 epochs.
   - Achieved accuracy of 0.92.
4. Technology Stack:
   - Python, PennyLane, PyTorch, scikit-learn, NumPy.
   - Quantum backend: default.qubit simulator.

CONCLUSION

This experiment demonstrates that on structured datasets, quantum-enhanced learning can perform on par with or even better than classical baselines. In order to handle complex images, future work will involve integrating classical CNN feature extractors before the quantum layer, increasing the number of qubits, and deploying the model on actual IBMQ hardware.
The project demonstrates how the next phase of effective AI may be defined by quantum-classical synergy.

APPENDICES

1. ☐ **Code Repository: [Planckd2025-HackyGo]**
2. ☐ **Results Folder: Includes accuracy logs and plots.**
3. ☐ **Dependencies: Listed in requirements.txt**
4. ☐ **Libraries Used: PennyLane, scikit-learn, Torch, NumPy, Matplotlib**