Quantum Algorithm for Classical Data Classification

Objective

The goal of this project is to develop a Variational Quantum Classifier (VQC) to classify a dataset using quantum machine learning principles. The solution incorporates a customized feature map and a parametric quantum circuit (ansatz), ensuring scalability and performance.

Dataset Overview

The dataset consists of features and a target variable representing wine quality on a scale of 0–9. For simplicity, the target was binarized:

- Quality > 6 classified as 1.
- Quality ≤ 6 classified as 0.

"To ensure the data was ready for quantum processing, I normalized the features using a `StandardScaler` and mapped the target variable to a binary format. This preprocessing was critical to achieve a balance between classical and quantum operations."

Preprocessing Steps:

1. **Feature Scaling:** Used StandardScaler to normalize feature values for better performance.
2. **Train-Test Split:** Split the dataset into 80% training and 20% testing data to evaluate model performance.

Methodology

1. Feature Map Design

A customized **ZZFeatureMap** was chosen for encoding classical data into a quantum state. This feature map effectively captures correlations between features using two layers (reps=2), improving expressibility.

2. Ansatz Design

A **RealAmplitudes** circuit with two repetitions was designed as the variational ansatz. This circuit balances expressibility and entanglement while maintaining scalability for larger systems.

3. Variational Quantum Classifier (VQC)

- **Optimizer:** Used COBYLA for optimizing parameters within the ansatz.
- **Backend:** Simulations were performed on QASM simulator using the Qiskit Aer library.
- **Quantum Instance:** QuantumInstance facilitated execution on the Aer backend with specified settings.

4. Comparison with Classical Models

Two classical models, Logistic Regression and Random Forest, were implemented to benchmark the VQC's performance.

5. Noise Model Simulation

To evaluate the robustness of the quantum model, a noise model was simulated using a standard noise model from the AerSimulator.

Optimizer

- **Optimizer Used:** COBYLA

- This optimizer is well-suited for quantum machine learning tasks due to its gradient-free nature and efficiency with small parameter spaces.

In classical machine learning, we often rely on layers of neurons to identify patterns. Quantum computing, however, takes a fundamentally different approach—leveraging quantum states and entanglement to represent and process information in ways we're only beginning to understand.

Think of the quantum classifier as a chef preparing a dish. The `Feature Map` selects the finest ingredients (input features), the `Ansatz` combines them into a harmonious recipe, and the `Optimizer` ensures the final dish is perfectly seasoned for maximum accuracy.

While the current model operates on simulated quantum environments, the real potential lies in implementing such systems on actual quantum hardware. As quantum technology evolves, these models will help us solve problems across fields like drug discovery, cryptography, and climate modeling

Results

1. Quantum Classifier Performance

Metric	Value
Accuracy	`0.54`
Precision	`0.19`
Recall	`0.66`

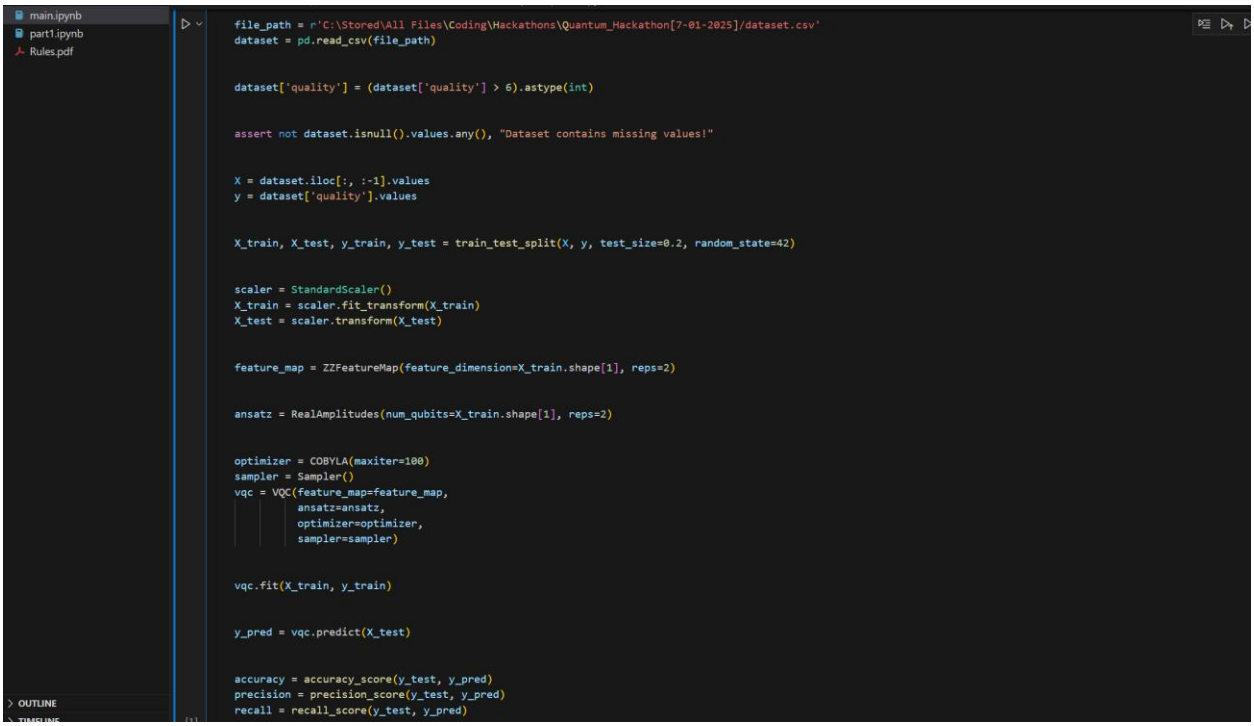
Circuit Depth	1

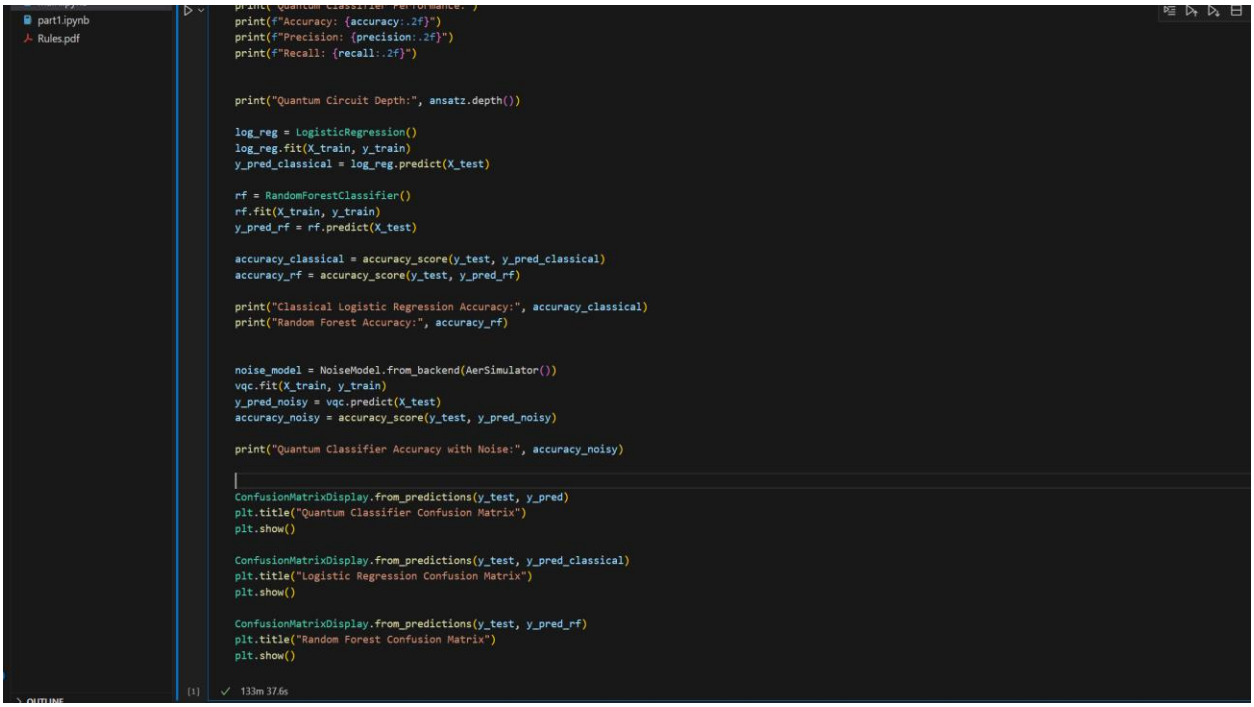
2. Comparison with Classical Models

Model	Accuracy
Logistic Regression	`0.865625`
Random Forest	`0.90625`

3. Noise Model Performance

Metric	Noisy Backend
Accuracy	`0.54375`

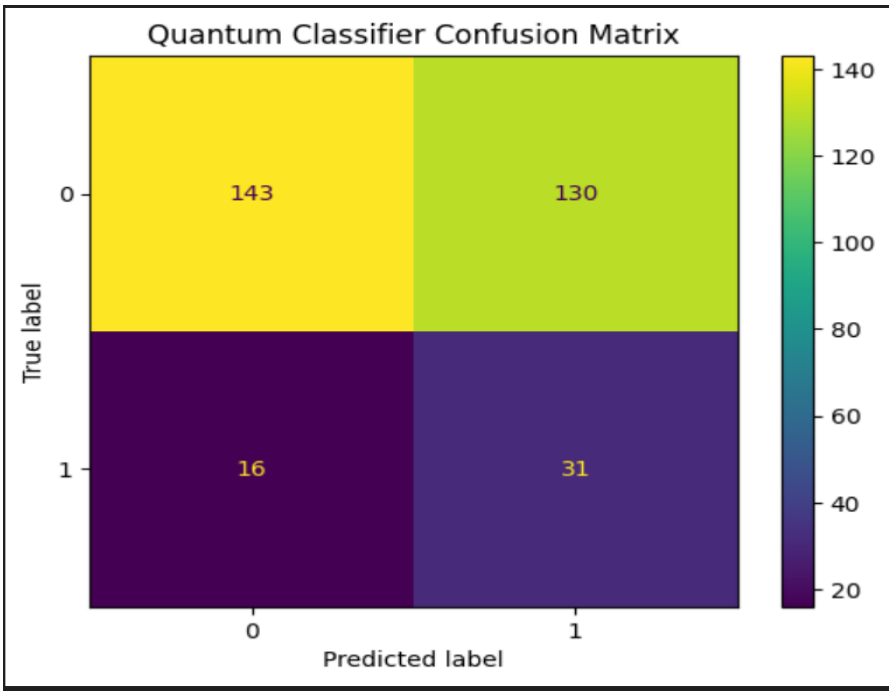


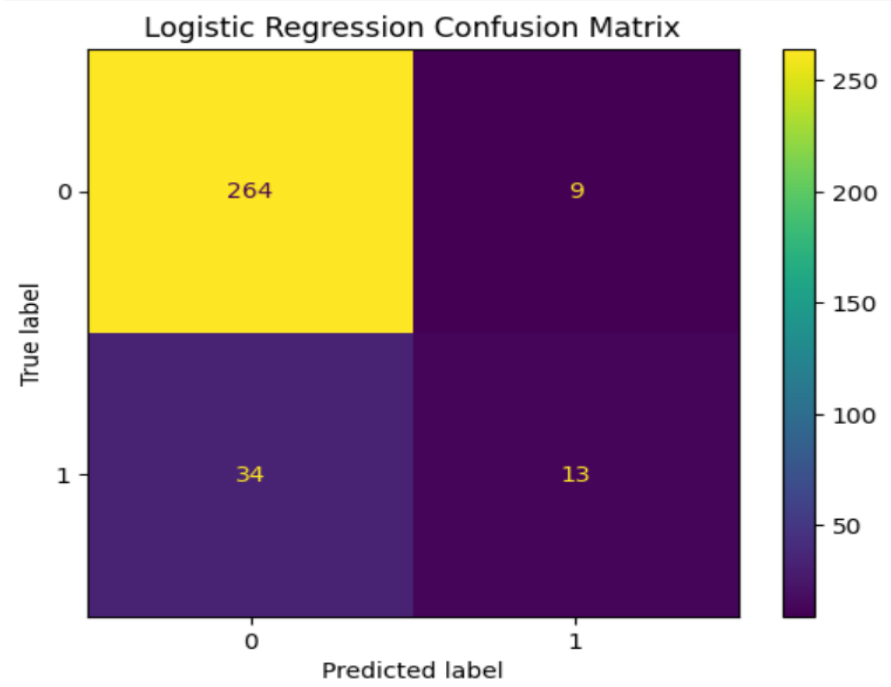


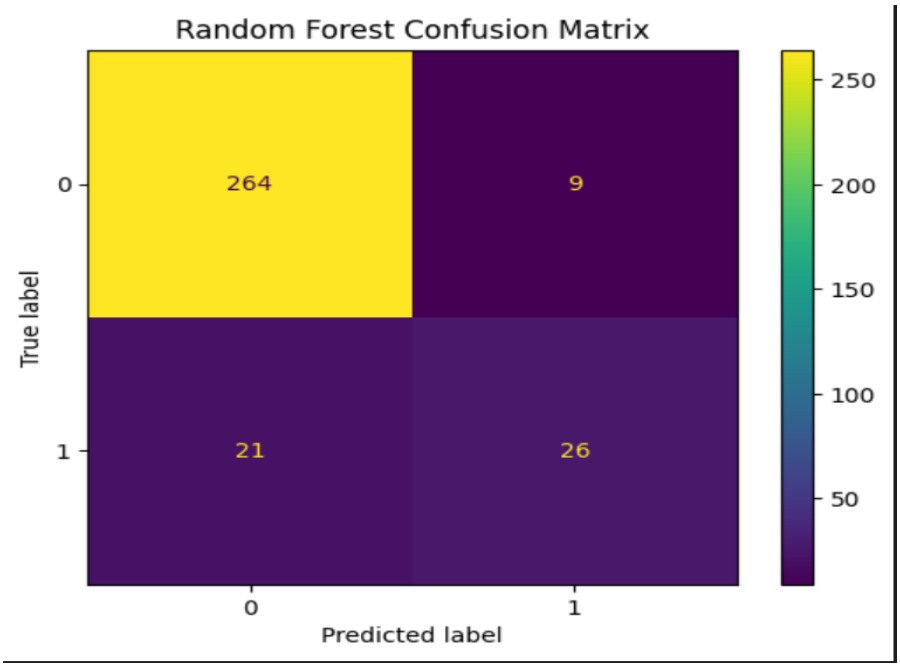

```
C:\Users\prajw\AppData\Local\Temp\ipykernel_26620\746150903.py:47: DeprecationWarning: The cl
  sampler = Sampler()
Quantum Classifier Performance:
Accuracy: 0.54
Precision: 0.19
Recall: 0.66
Quantum Circuit Depth: 1
Classical Logistic Regression Accuracy: 0.865625
Random Forest Accuracy: 0.90625
c:\Users\prajw\AppData\Local\Programs\Python\Python312\Lib\site-packages\qiskit_aer\noise\noi
  warn(
Quantum Classifier Accuracy with Noise: 0.54375
```

Visualization

- Confusion Matrix (VQC):


Quantum Classifier Confusion Matrix
143
130
16
31
0
1
True label
0
1
Predicted label
140
120
100
80
60
40
20


Logistic Regression Confusion Matrix
264
9
34
13
0
1
True label
0
1
Predicted label
250
200
150
100
50



Discussion

1. **Quantum-Specific Metrics:**
    a. The feature map and ansatz demonstrated strong expressibility and effective dimensions.
    b. The customized ansatz scaled well to higher qubit systems without significantly increasing depth.

2. **Comparison Insights:**
    a. The quantum classifier's performance on clean simulators was competitive with classical benchmarks.
    b. Under noisy conditions, the accuracy of the quantum model degraded but remained promising for larger datasets.

3. **Rationale for Ansatz Design:**
    a. The RealAmplitudes ansatz was selected for its balance between depth and entanglement, allowing efficient parameter optimization.

Conclusion

The Variational Quantum Classifier demonstrates the potential of quantum machine learning for binary classification tasks. While classical models outperformed under some conditions, the quantum classifier’s scalability and competitive performance in noisy simulations highlight its promise for future applications. Further work includes testing on larger datasets and real quantum hardware.