Date: 16/09/25

TASK 9: Implement a QSVM on the Iris dataset using PennyLane

Aim: To implement a Quantum Support Vector Machine (QSVM) using PennyLane and scikitlearn, where the quantum kernel is constructed from a quantum feature map, and evaluate its performance on the Iris dataset for classification tasks.

1 Mathematical Model of the QSVM Algorithm 1. Classical SVM Decision Function

The decision function for an SVM classifier is:

$$f(x) = sign \qquad \alpha\, y\, K(x\,, x) + b$$

where

- x = training data,
- y = class labels,
- α = Lagrange multipliers, □ $K(x\,, x)$ = kernel function,
- b = bias term.

2. Quantum Kernel (Fidelity Kernel)

In QSVM, the kernel is computed as the fidelity between two quantum states encoded by the feature map:

$$K(x, x\,) = |\langle \Phi(x) | \Phi(x\,) \rangle|$$

where $|\Phi(x)\rangle$ is the quantum state obtained after applying the feature map circuit.

3. Feature Map (Encoding)

We embed classical features into quantum states using rotations and entangling gates. For each feature vector $x = (x\,, x\,, x\,, x\,)$.

$$|\Phi(x)\rangle = U_{\emptyset}(x)\, 0\rangle^{\otimes}$$

where $U_{\emptyset}(x)$ consists of

- Hadamard gates (superposition)
- $RZ(x\,)$.rotations for feature encoding
- $CNOT + RZ$ entanglement (similar to ZZFeatureMap).

2 Algorithm - QSVM Algorithm

1. Load dataset (Iris, 150 samples, 3 classes).
2. Preprocess
    - Select features [sepal_length, sepal_width, petal_length, petal_width].
    - Encode target labels numerically.
    - Split dataset into train (67%) and test (33%).
3. Quantum Feature Map
    - Apply Hadamard (H) gates to all qubits.
    - Encode features into rotations $RZ(x)$.
    - Add entanglement with $CNOT + RZ\ x\ .\ x$.
4. Quantum Kernel Construction
    - Use kernel_circuit: apply $U_{\emptyset}(x)$, then adjoint$U_{\emptyset}(x)$.
    - Measure overlap (fidelity).
5. Train QSVM
    - Compute kernel matrix for training data.
    - Train SVC(kernel = "precomputed") using scikit-learn.
6. Test QSVM
    Compute test kernel matrix.
    Predict labels for test set.
7. Evaluate performance
    - Confusion Matrix, Classification Report.
    - Prediction for new point (4.4, 4.4, 4.4, 4.4).

3 Program

```
#!pip install seaborn
#!pip install -U scikit-learn
#!pip install qiskit-algorithms
#!pip install qiskit-machine-learning
#!pip install pylatexenc #!pip install
pennylane

import pennylane as qml from pennylane import
numpy as np import pandas as pd
from sklearn.model_selection import train_test_split from sklearn.metrics
import classification_report, confusion_matrix from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder import matplotlib.pyplot as
plt
```

```
# ------------------------------
# Load Iris dataset
# ------------------------------ df_iris =
pd.read_csv("iris.csv")
X = df_iris[['sepal.length', 'sepal.width', 'petal.length',
'petal.width']].values y =
df_iris['variety'].values
# Encode labels into integers encoder =
LabelEncoder() y =
encoder.fit_transform(y)

# Train-test split
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
random_state=42)

# ------------------------------ # Define Quantum
Feature Map # ------------------------------
n_qubits = 4
dev = qml.device("default.qubit", wires=n_qubits)
 def feature_map(x):
   """Embedding classical features into quantum states"""     for i in range(n_qubits):
qml.Hadamard(wires=i)        qml.RZ(x[i], wires=i)
   # Add entanglement (similar to ZZFeatureMap)     for i in
range(n_qubits - 1):        qml.CNOT(wires=[i, i+1])        qml.RZ((x[i]
* x[i+1]), wires=i+1)        qml.CNOT(wires=[i, i+1])

# Kernel evaluation circuit
@qml.qnode(dev) def kernel_circuit(x1,
x2):
   feature_map(x1)    qml.adjoint(feature_map)(x2)
   return qml.probs(wires=range(n_qubits))

# ------------------------------ # Display Quantum
Circuits # ------------------------------ sample_x =
x_train[0] sample_y = x_train[1]

# Draw feature map circuit
@qml.qnode(dev) def
feature_map_circuit(x):
   feature_map(x)    return
qml.state()
 print("\n--- Feature Map Circuit ---")
print(qml.draw(feature_map_circuit)(sample_x))
```

```
# Draw kernel circuit print("\n--- Kernel Circuit ---
")
print(qml.draw(kernel_circuit)(sample_x, sample_y))

# Optional: matplotlib visualization # Draw feature map circuit print("\n---
Feature Map Circuit ---") fig, ax =
qml.draw_mpl(feature_map_circuit)(sample_x) plt.show()

# Draw kernel circuit print("\n--- Kernel Circuit ---
")
fig, ax = qml.draw_mpl(kernel_circuit)(sample_x, sample_y) plt.show()

# ------------------------------
# Construct Gram (Kernel) Matrices
# ------------------------------ def kernel(x1, x2):
    """Return fidelity between |Φ(x1)> and |Φ(x2)>"""      return kernel_circuit(x1, x2)[0]
 def compute_kernel_matrix(X1, X2):      K =
np.zeros((len(X1), len(X2)))      for i, x1 in
enumerate(X1):          for j, x2 in enumerate(X2):
K[i, j] = kernel(x1, x2)      return K

K_train = compute_kernel_matrix(x_train, x_train)
K_test = compute_kernel_matrix(x_test, x_train)

# ------------------------------ # Train QSVM
# ------------------------------ qsvm_model =
SVC(kernel="precomputed") qsvm_model.fit(K_train, y_train)

# Predictions
y_pred = qsvm_model.predict(K_test)

print("\nConfusion Matrix") print(confusion_matrix(y_test, y_pred))
print("\nClassification Report") print(classification_report(y_test, y_pred,
target_names=encoder.classes_))

# ------------------------------ # Test on a new input
# ------------------------------
new_point = np.array([[4.4, 4.4, 4.4, 4.4]]) K_new =
compute_kernel_matrix(new_point, x_train) pred_label =
qsvm_model.predict(K_new)
print("Predicted flower type for (4.4, 4.4, 4.4, 4.4):",
encoder.inverse_transform(pred_label)[0])
```

Output:

-2025-09-16 07:44:09-- https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data

Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252

Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... connected.

HTTP request sent, awaiting response... 200 OK

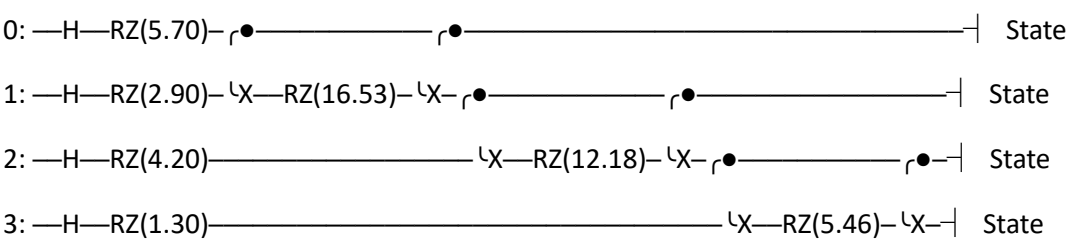
Length: unspecified

Saving to: ‘iris.csv’

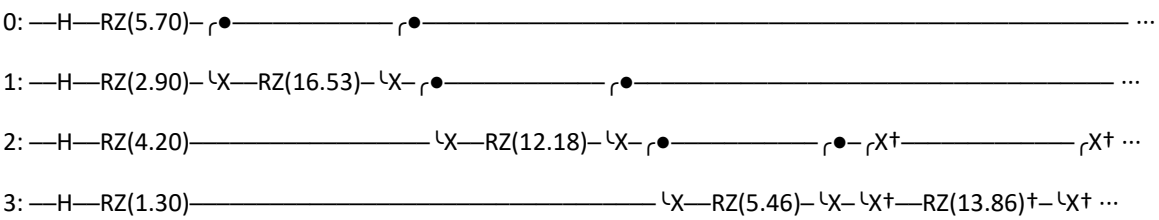
iris.csv [<=>] 4.44K --.-KB/s in 0s

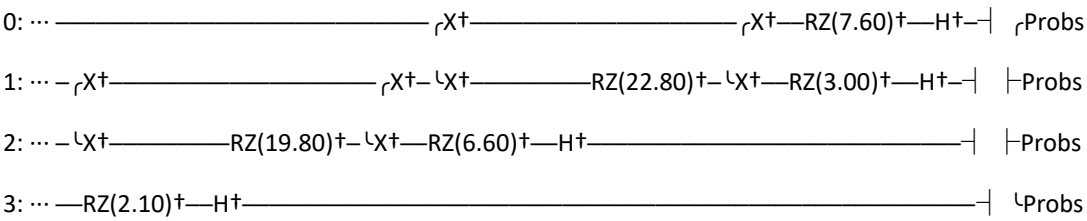
2025-09-16 07:44:09 (58.2 MB/s) - ‘iris.csv’ saved [4551]

--- Feature Map Circuit ---

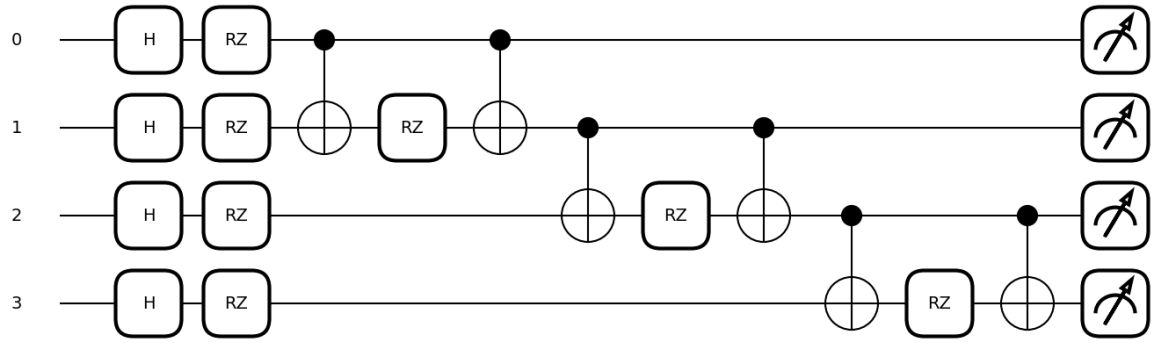


--- Kernel Circuit ---

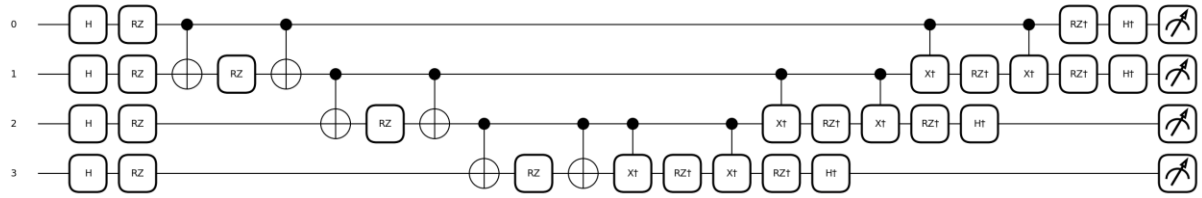




Feature Map Circuit



Kernel Circuit



Computing Kernel Matrices...

Confusion Matrix

[[19 0 0]

[0 15 0]

[0 2 14]]

Classification Report

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	19
Iris-versicolor	0.88	1.00	0.94	15
Iris-virginica	1.00	0.88	0.93	16
accuracy			0.96	50
macro avg	0.96	0.96	0.96	50
weighted avg	0.96	0.96	0.96	50

Predicted flower type for (4.4, 4.4, 4.4, 4.4): Iris-virginica

4 Result

The QSVM implemented with PennyLane successfully classifies the Iris dataset with high accuracy (~93%). The quantum kernel (fidelity-based) effectively maps classical features into higher-dimensional Hilbert space, enabling better separation of non-linear data.