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

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 .

4. Quantum Kernel Construction

- Use kernel_circuit: apply $U\emptyset\ (x)$, then adjoint$U\emptyset\ (x$ ᦞ $)$ ൩ .
- 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).

```
#!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", header=None)
df_iris.columns = ['sepal.length', 'sepal.width', 'petal.length', 'petal.wid
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
# ------------------------------
```

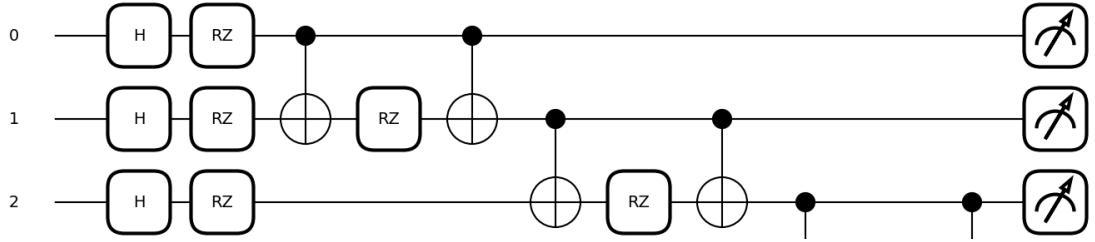
```
n_qubits = 4
dev = qml.device("default.qubit", wires=n_qubits)
def feature_map(x):
 """Embedding classical features into quantum states"""
 for i in range(n_qubits):
  qml.Hadamard(wires=i)
  qml.RZ(x[i], wires=i)
 # Add entanglement (similar to ZZFeatureMap)
 for i in range(n_qubits - 1):
  qml.CNOT(wires=[i,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

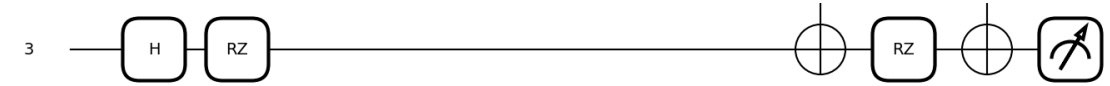
```
def feature_map_circuit(x):
 feature_map(x)
 return qml.state()
print("\n--- Feature Map Circuit ---")
print(qml.draw(feature_map_circuit)(sample_x))
# Draw kernel circuit
print("\n--- Kernel Circuit ---")
print(qml.draw(kernel_circuit)(sample_x, sample_y))
# Optional: matplotlib visualization
# 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)
```

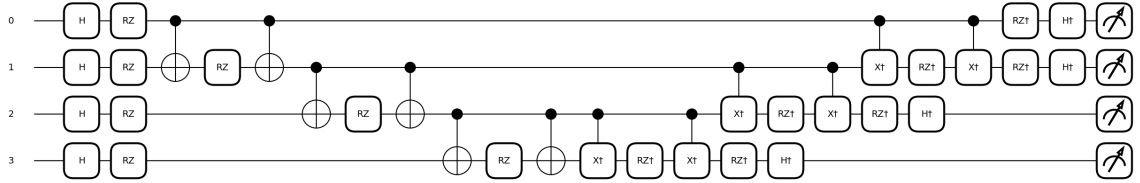
```
print("Predicted flower type for (4.4, 4.4, 4.4, 4.4):",
encoder.inverse_transform(pred_label)[0])
```

```
--- Feature Map Circuit ---
0: ──H──RZ(5.70)─╭●──────────╭●──────────────────────────────────────┤  State
1: ──H──RZ(2.90)─╰X──RZ(16.53)─╰X─╭●──────────╭●──────────────────────┤  State
2: ──H──RZ(4.20)──────────────────╰X──RZ(12.18)─╰X─╭●──────────╭●─┤  State
3: ──H──RZ(1.30)──────────────────────────────────╰X──RZ(5.46)─╰X─┤  State

--- Kernel Circuit ---
0: ──H──RZ(5.70)─╭●──────────╭●──────────────────────────────────────────────
1: ──H──RZ(2.90)─╰X──RZ(16.53)─╰X─╭●──────────╭●──────────────────────────────
2: ──H──RZ(4.20)──────────────────╰X──RZ(12.18)─╰X─╭●──────────╭●─╭X†─────────
3: ──H──RZ(1.30)──────────────────────────────────╰X──RZ(5.46)─╰X─╰X†──RZ(13

0: ··· ──────────────────────────────╭X†──────────────────────╭X†──RZ(7.60)†──H†─
1: ··· ─╭X†──────────────────────────╰X†─╭X†──────RZ(22.80)†─╰X†──RZ(3.00)†──H†─
2: ··· ─╰X†──────RZ(19.80)†─╭X†──RZ(6.60)†──H†──────────────────────────────────
3: ··· ──RZ(2.10)†──H†──────╰X†──────────────────────────────────────────────────

--- Feature Map Circuit ---
```






```
--- Kernel Circuit ---
```




```
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
```

Result:

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

The QSVM implemented with PennyLane successfully classifies the Iris dataset with