

Task_III

March 26, 2021

```
[1]: import tensorflow as tf
import tensorflow_quantum as tfq

import cirq
import sympy
import numpy as np

%matplotlib inline
import matplotlib.pyplot as plt
from cirq.contrib.svg import SVGCircuit
```

```
[2]: # Load the data.
with np.load("ML4SCI_GSoC/QMLHEP/qcnn/electron-photon.npz") as data:
    train_examples = data['x_train'].reshape(-1, 32, 32, 1)
    train_labels = data['y_train']
    test_examples = data['x_test'].reshape(-1, 32, 32, 1)
    test_labels = data['y_test']
```

```
[3]: # Crop the image to make the calculations more feasible.
x_train_crop = train_examples[:, 15:19, 14:18, :]
x_test_crop = test_examples[:, 15:19, 14:18, :]
print(x_train_crop.shape)
print(x_test_crop.shape)
```

(100, 4, 4, 1)

(100, 4, 4, 1)

```
[4]: # Encode the values in a circuit by rotating the qubits by pixel values
def convert_to_circuit(image):
    values = np.ndarray.flatten(image)
    qubits = cirq.GridQubit.rect(4, 4)
    circuit = cirq.Circuit()
    for i, value in enumerate(values):
        if value:
            circuit.append(cirq.X(qubits[i]))
    return circuit
```

```
x_train_circ = [convert_to_circuit(x) for x in x_train_crop]
x_test_circ = [convert_to_circuit(x) for x in x_test_crop]
```

```
[5]: # Convert the circuits to tensors for use with TensorFlow Quantum
x_train_tfcirc = tfq.convert_to_tensor(x_train_circ)
x_test_tfcirc = tfq.convert_to_tensor(x_test_circ)
```

```
[6]: # Create a cluster state circuit.
def cluster_state_circuit(bits):
    """Return a cluster state on the qubits in `bits`."""
    circuit = cirq.Circuit()
    circuit.append(cirq.H.on_each(bits))
    for this_bit, next_bit in zip(bits, bits[1:] + [bits[0]]):
        circuit.append(cirq.CZ(this_bit, next_bit))
    return circuit
```

```
[8]: # Convolution operation can be achieved using parameterised unitaries or random
      ↪ parameterised circuits.
def one_qubit_unitary(bit, symbols):
    return cirq.Circuit(
        cirq.X(bit)**symbols[0],
        cirq.Y(bit)**symbols[1],
        cirq.Z(bit)**symbols[2])

def two_qubit_unitary(bits, symbols):
    circuit = cirq.Circuit()
    circuit += one_qubit_unitary(bits[0], symbols[0:3])
    circuit += one_qubit_unitary(bits[1], symbols[3:6])
    circuit += [cirq.ZZ(*bits)**symbols[6]]
    circuit += [cirq.YY(*bits)**symbols[7]]
    circuit += [cirq.XX(*bits)**symbols[8]]
    circuit += one_qubit_unitary(bits[0], symbols[9:12])
    circuit += one_qubit_unitary(bits[1], symbols[12:])
    return circuit

def two_qubit_pool(source_qubit, sink_qubit, symbols):
    pool_circuit = cirq.Circuit()
    sink_basis_selector = one_qubit_unitary(sink_qubit, symbols[0:3])
    source_basis_selector = one_qubit_unitary(source_qubit, symbols[3:6])
    pool_circuit.append(sink_basis_selector)
    pool_circuit.append(source_basis_selector)
    pool_circuit.append(cirq.CNOT(control=source_qubit, target=sink_qubit))
    pool_circuit.append(sink_basis_selector**-1)
    return pool_circuit
```

```
[9]: # Create a circuit for performing a convolution operation.
def quantum_conv_circuit(bits, symbols):
    circuit = cirq.Circuit()
    for first, second in zip(bits[0::2], bits[1::2]):
        circuit += two_qubit_unitary([first, second], symbols)
    for first, second in zip(bits[1::2], bits[2::2] + [bits[0]]):
        circuit += two_qubit_unitary([first, second], symbols)
    return circuit
```

```
[10]: # Create a circuit for performing a pooling operation.
def quantum_pool_circuit(source_bits, sink_bits, symbols):
    circuit = cirq.Circuit()
    for source, sink in zip(source_bits, sink_bits):
        circuit += two_qubit_pool(source, sink, symbols)
    return circuit
```

```
[11]: # Create a circuit using the above circuits. To achieve 3 sets of convolutions
      ↪ and pooling operations.
def create_model_circuit(qubits):
    model_circuit = cirq.Circuit()
    symbols = sympy.symbols('qconv0:63')

    model_circuit += quantum_conv_circuit(qubits, symbols[0:15])
    model_circuit += quantum_pool_circuit(qubits[:4], qubits[4:],
                                          symbols[15:21])
    model_circuit += quantum_conv_circuit(qubits[4:], symbols[21:36])
    model_circuit += quantum_pool_circuit(qubits[4:6], qubits[6:],
                                          symbols[36:42])
    model_circuit += quantum_conv_circuit(qubits[6:], symbols[42:57])
    model_circuit += quantum_pool_circuit([qubits[6]], [qubits[7]],
                                          symbols[57:63])

    return model_circuit

cluster_state_bits = cirq.GridQubit.rect(4, 4)
readout_operators = cirq.Z(cluster_state_bits[-1])

# Convert the model circuit to a Keras model so that it can be trained.
excitation_input = tf.keras.Input(
    shape=(),
    dtype=tf.dtypes.string
)
cluster_state = tfq.layers.AddCircuit()(
    excitation_input,
    ↪
    ↪prepend=cluster_state_circuit(cluster_state_bits)
```

```

    )

quantum_model = tfq.layers.PQC(create_model_circuit(cluster_state_bits),
    ↪readout_operators)(cluster_state)

qcnm_model = tf.keras.Model(inputs=[excitation_input], outputs=[quantum_model])

```

('Failed to import pydot. You must `pip install pydot` and install graphviz (<https://graphviz.gitlab.io/download/>), ', 'for `pydotprint` to work.')

```

[12]: # Compile the model for binary classification.
qcnm_model.compile(optimizer=tf.keras.optimizers.Adam(lr=0.02),
                  loss=tf.losses.binary_crossentropy,
                  metrics='accuracy')

history = qcnm_model.fit(x=x_train_tfcirc, y=train_labels, batch_size=16,
    ↪epochs=25, validation_data=(x_train_tfcirc, test_labels))

```

```

Epoch 1/25
7/7 [=====] - 3s 476ms/step - loss: 2.7855 - accuracy:
0.4400 - val_loss: 1.3676 - val_accuracy: 0.5400
Epoch 2/25
7/7 [=====] - 3s 452ms/step - loss: 1.6641 - accuracy:
0.4400 - val_loss: 1.1344 - val_accuracy: 0.5400
Epoch 3/25
7/7 [=====] - 3s 462ms/step - loss: 1.3086 - accuracy:
0.4400 - val_loss: 1.3065 - val_accuracy: 0.5400
Epoch 4/25
7/7 [=====] - 3s 470ms/step - loss: 1.6251 - accuracy:
0.4400 - val_loss: 1.3198 - val_accuracy: 0.5400
Epoch 5/25
7/7 [=====] - 3s 450ms/step - loss: 1.5702 - accuracy:
0.4400 - val_loss: 0.9831 - val_accuracy: 0.5400
Epoch 6/25
7/7 [=====] - 3s 451ms/step - loss: 1.5096 - accuracy:
0.4400 - val_loss: 1.2661 - val_accuracy: 0.5400
Epoch 7/25
7/7 [=====] - 3s 471ms/step - loss: 1.4670 - accuracy:
0.4400 - val_loss: 1.1251 - val_accuracy: 0.5400
Epoch 8/25
7/7 [=====] - 3s 467ms/step - loss: 1.3050 - accuracy:
0.4400 - val_loss: 1.0084 - val_accuracy: 0.5400
Epoch 9/25
7/7 [=====] - 3s 464ms/step - loss: 1.1559 - accuracy:
0.4400 - val_loss: 0.9045 - val_accuracy: 0.5400
Epoch 10/25
7/7 [=====] - 3s 472ms/step - loss: 1.0173 - accuracy:

```

0.4400 - val_loss: 0.8142 - val_accuracy: 0.5400
 Epoch 11/25
 7/7 [=====] - 3s 470ms/step - loss: 0.9173 - accuracy:
 0.4400 - val_loss: 0.7591 - val_accuracy: 0.5400
 Epoch 12/25
 7/7 [=====] - 3s 475ms/step - loss: 0.8433 - accuracy:
 0.4400 - val_loss: 0.7205 - val_accuracy: 0.5400
 Epoch 13/25
 7/7 [=====] - 3s 465ms/step - loss: 0.7915 - accuracy:
 0.4400 - val_loss: 0.7049 - val_accuracy: 0.5400
 Epoch 14/25
 7/7 [=====] - 3s 462ms/step - loss: 0.7603 - accuracy:
 0.4400 - val_loss: 0.6984 - val_accuracy: 0.5400
 Epoch 15/25
 7/7 [=====] - 3s 459ms/step - loss: 0.7406 - accuracy:
 0.4700 - val_loss: 0.6962 - val_accuracy: 0.4100
 Epoch 16/25
 7/7 [=====] - 3s 461ms/step - loss: 0.7293 - accuracy:
 0.4600 - val_loss: 0.6960 - val_accuracy: 0.4500
 Epoch 17/25
 7/7 [=====] - 3s 454ms/step - loss: 0.7260 - accuracy:
 0.4700 - val_loss: 0.7076 - val_accuracy: 0.4500
 Epoch 18/25
 7/7 [=====] - 3s 461ms/step - loss: 0.7205 - accuracy:
 0.4700 - val_loss: 0.7092 - val_accuracy: 0.4500
 Epoch 19/25
 7/7 [=====] - 3s 466ms/step - loss: 0.7184 - accuracy:
 0.4700 - val_loss: 0.7042 - val_accuracy: 0.4500
 Epoch 20/25
 7/7 [=====] - 3s 456ms/step - loss: 0.7146 - accuracy:
 0.4700 - val_loss: 0.6955 - val_accuracy: 0.4500
 Epoch 21/25
 7/7 [=====] - 3s 456ms/step - loss: 0.7130 - accuracy:
 0.4700 - val_loss: 0.6996 - val_accuracy: 0.4500
 Epoch 22/25
 7/7 [=====] - 3s 445ms/step - loss: 0.7178 - accuracy:
 0.4700 - val_loss: 0.6862 - val_accuracy: 0.4500
 Epoch 23/25
 7/7 [=====] - 3s 449ms/step - loss: 0.7076 - accuracy:
 0.4700 - val_loss: 0.7055 - val_accuracy: 0.4500
 Epoch 24/25
 7/7 [=====] - 3s 454ms/step - loss: 0.7098 - accuracy:
 0.4900 - val_loss: 0.7066 - val_accuracy: 0.4900
 Epoch 25/25
 7/7 [=====] - 3s 448ms/step - loss: 0.7058 - accuracy:
 0.5100 - val_loss: 0.6903 - val_accuracy: 0.4900

```
[13]: # Create a smaller circuit for hybrid model.
readouts = [cirq.Z(bit) for bit in cluster_state_bits[4:]]
def multi_readout_model_circuit(qubits):
    model_circuit = cirq.Circuit()
    symbols = sympy.symbols('qconv0:21')
    model_circuit += quantum_conv_circuit(qubits, symbols[0:15])
    model_circuit += quantum_pool_circuit(qubits[:4], qubits[4:],
                                         symbols[15:21])

    return model_circuit

[14]: # Use the above circuit to create a Keras model with multiple convolution and
      ↪pooling layers.
excitation_input_multi = tf.keras.Input(shape=(), dtype=tf.dtypes.string)

cluster_state_multi = tfq.layers.AddCircuit()(
    excitation_input_multi, prepend=cluster_state_circuit(cluster_state_bits))

quantum_model_multi1 = tfq.layers.PQC(
    multi_readout_model_circuit(cluster_state_bits),
    readouts)(cluster_state_multi)

quantum_model_multi2 = tfq.layers.PQC(
    multi_readout_model_circuit(cluster_state_bits),
    readouts)(cluster_state_multi)

quantum_model_multi3 = tfq.layers.PQC(
    multi_readout_model_circuit(cluster_state_bits),
    readouts)(cluster_state_multi)

# Concatenate the outputs and feed into a small classical dense network
concat_out = tf.keras.layers.concatenate(
    [quantum_model_multi1, quantum_model_multi2, quantum_model_multi3])

dense_1 = tf.keras.layers.Dense(8)(concat_out)

dense_2 = tf.keras.layers.Dense(1)(dense_1)

multi_qconv_model = tf.keras.Model(inputs=[excitation_input_multi],
                                   outputs=[dense_2])

[15]: # Compile and train the model.
multi_qconv_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.
      ↪02),
                           loss='binary_crossentropy',
                           metrics=['accuracy'])
```

```
hhistory = multi_qconv_model.fit(x=x_train_tfcirc, y=train_labels,  
    ↪ batch_size=16, epochs=25, validation_data=(x_train_tfcirc, test_labels))
```

```
Epoch 1/25  
7/7 [=====] - 2s 352ms/step - loss: 1.2440 - accuracy:  
0.5000 - val_loss: 0.7048 - val_accuracy: 0.5400  
Epoch 2/25  
7/7 [=====] - 2s 315ms/step - loss: 0.7420 - accuracy:  
0.4700 - val_loss: 0.7243 - val_accuracy: 0.4400  
Epoch 3/25  
7/7 [=====] - 2s 310ms/step - loss: 0.6930 - accuracy:  
0.5000 - val_loss: 0.7251 - val_accuracy: 0.4600  
Epoch 4/25  
7/7 [=====] - 2s 312ms/step - loss: 0.6926 - accuracy:  
0.5600 - val_loss: 0.6952 - val_accuracy: 0.4400  
Epoch 5/25  
7/7 [=====] - 2s 302ms/step - loss: 0.7292 - accuracy:  
0.5000 - val_loss: 0.6970 - val_accuracy: 0.4400  
Epoch 6/25  
7/7 [=====] - 2s 298ms/step - loss: 0.6830 - accuracy:  
0.5600 - val_loss: 0.7602 - val_accuracy: 0.4600  
Epoch 7/25  
7/7 [=====] - 2s 318ms/step - loss: 0.6917 - accuracy:  
0.5600 - val_loss: 0.7150 - val_accuracy: 0.4600  
Epoch 8/25  
7/7 [=====] - 2s 307ms/step - loss: 0.6791 - accuracy:  
0.5500 - val_loss: 0.7115 - val_accuracy: 0.4400  
Epoch 9/25  
7/7 [=====] - 2s 321ms/step - loss: 0.6806 - accuracy:  
0.5100 - val_loss: 0.7127 - val_accuracy: 0.4800  
Epoch 10/25  
7/7 [=====] - 2s 311ms/step - loss: 0.6738 - accuracy:  
0.5600 - val_loss: 0.7171 - val_accuracy: 0.4700  
Epoch 11/25  
7/7 [=====] - 2s 334ms/step - loss: 0.6652 - accuracy:  
0.5800 - val_loss: 0.7214 - val_accuracy: 0.4700  
Epoch 12/25  
7/7 [=====] - 2s 308ms/step - loss: 0.6735 - accuracy:  
0.5900 - val_loss: 0.8681 - val_accuracy: 0.4700  
Epoch 13/25  
7/7 [=====] - 2s 342ms/step - loss: 0.6532 - accuracy:  
0.5600 - val_loss: 0.7408 - val_accuracy: 0.4200  
Epoch 14/25  
7/7 [=====] - 2s 302ms/step - loss: 0.6579 - accuracy:  
0.4900 - val_loss: 0.9842 - val_accuracy: 0.4800  
Epoch 15/25  
7/7 [=====] - 2s 308ms/step - loss: 0.6539 - accuracy:
```

```

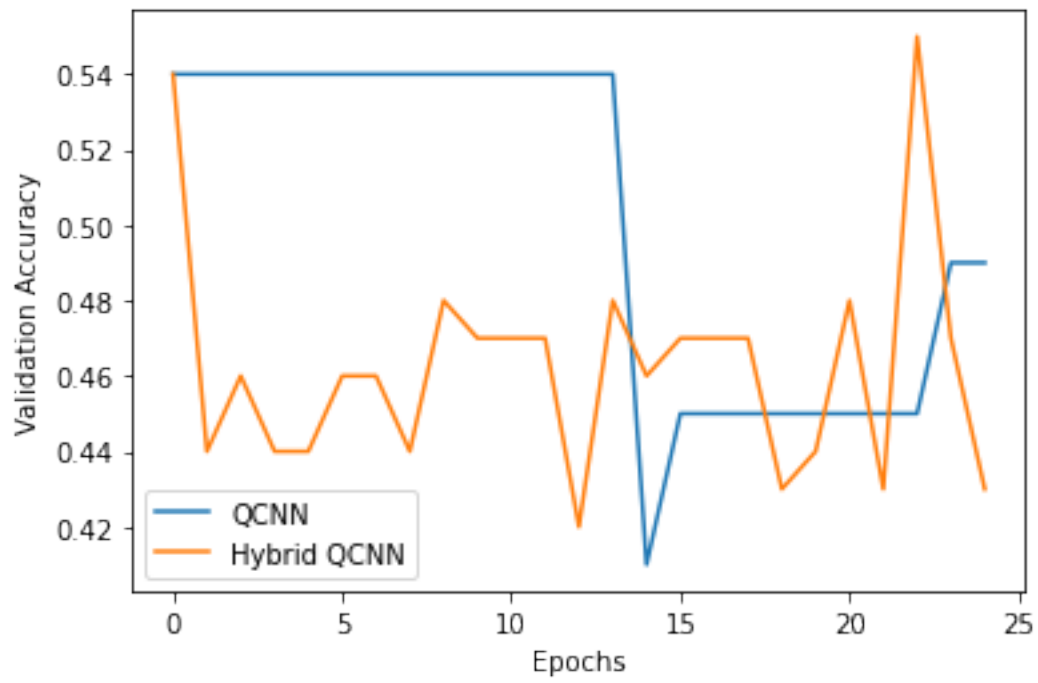
0.5800 - val_loss: 0.9877 - val_accuracy: 0.4600
Epoch 16/25
7/7 [=====] - 2s 323ms/step - loss: 0.6491 - accuracy:
0.5900 - val_loss: 0.9879 - val_accuracy: 0.4700
Epoch 17/25
7/7 [=====] - 2s 323ms/step - loss: 0.6556 - accuracy:
0.5100 - val_loss: 0.9803 - val_accuracy: 0.4700
Epoch 18/25
7/7 [=====] - 2s 338ms/step - loss: 0.6441 - accuracy:
0.5800 - val_loss: 0.9938 - val_accuracy: 0.4700
Epoch 19/25
7/7 [=====] - 2s 312ms/step - loss: 0.6359 - accuracy:
0.5800 - val_loss: 1.0040 - val_accuracy: 0.4300
Epoch 20/25
7/7 [=====] - 2s 307ms/step - loss: 0.6653 - accuracy:
0.5100 - val_loss: 0.9828 - val_accuracy: 0.4400
Epoch 21/25
7/7 [=====] - 2s 314ms/step - loss: 0.6397 - accuracy:
0.5600 - val_loss: 1.1381 - val_accuracy: 0.4800
Epoch 22/25
7/7 [=====] - 2s 325ms/step - loss: 0.6712 - accuracy:
0.6000 - val_loss: 1.1184 - val_accuracy: 0.4300
Epoch 23/25
7/7 [=====] - 2s 318ms/step - loss: 0.6404 - accuracy:
0.5600 - val_loss: 0.9751 - val_accuracy: 0.5500
Epoch 24/25
7/7 [=====] - 2s 301ms/step - loss: 0.6486 - accuracy:
0.5800 - val_loss: 1.0064 - val_accuracy: 0.4700
Epoch 25/25
7/7 [=====] - 2s 316ms/step - loss: 0.6786 - accuracy:
0.5800 - val_loss: 0.9769 - val_accuracy: 0.4300

```

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[16]: # Plot the comparative accuracies of both models.
plt.plot(history.history['val_accuracy'], label='QCNN')
plt.plot(hhistory.history['val_accuracy'], label='Hybrid QCNN')
plt.xlabel('Epochs')
plt.legend()
plt.ylabel('Validation Accuracy')
plt.show()

```

[]: