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Task III: Quantum Convolutional Neural Network (QCNN) Part

Your task is to setup and apply a quantum convolutional neural network (QCNN) on particle physics data to perform binary classification on two types of objects (electrons and photons). You should use TFQ for this task.
The electron-photon dataset (which can be found here) contains 100 samples for training and another 100 for testing, laid out as follows:

- data["x_train"]: Training dataset of 100 32x32 images containing the particles' energy (100, 32, 32)
- data["y_train"]:" Training labels, 0 = "photon", 1 = "electron" (100,)
- data["x_test"]: Test dataset of 100 32x32 images containing the particles' energy (100, 32, 32)
- data["y_test"]:" Test labels, 0 = "photon", 1 = "electron" (100,)

The dataset labels are labelled 0 for photons and 1 for electrons. Your task is to implement a QCNN model in Tensorflow Quantum that uses this dataset's input and performs binary classification. Please feel free to experiment with different ways of encoding the classical data inputs into the qubits.
Specifically, show that the model fits the dataset and that your training loss decreases over time. (Given the small dataset size, we will not be focusing on the accuracy of your model).

Downloading the dataset

In [1]:
```
!wget https://github.com/ML4SCI/ML4SCI_GSoC/blob/main/QMLHEP/qcnn/electron-photon.npz?raw=true -O electron-photon.npz
```

```
--2021-03-19 15:06:37--  https://github.com/ML4SCI/ML4SCI_GSoC/blob/main/QMLHEP/qcnn/electron-photon.npz?raw=true
Resolving github.com (github.com)... 140.82.114.3
Connecting to github.com (github.com)|140.82.114.3|:443... connected.
HTTP request sent, awaiting response... 302 Found
Location: https://github.com/ML4SCI/ML4SCI_GSoC/raw/main/QMLHEP/qcnn/electron-photon.npz [following]
--2021-03-19 15:06:38--  https://github.com/ML4SCI/ML4SCI_GSoC/raw/main/QMLHEP/qcnn/electron-photon.npz
Reusing existing connection to github.com:443.
HTTP request sent, awaiting response... 302 Found
Location: https://raw.githubusercontent.com/ML4SCI/ML4SCI_GSoC/main/QMLHEP/qcnn/electron-photon.npz [following]
--2021-03-19 15:06:38--  https://raw.githubusercontent.com/ML4SCI/ML4SCI_GSoC/main/QMLHEP/qcnn/electron-photon.npz
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 821002 (802K) [application/octet-stream]
Saving to: 'electron-photon.npz'

electron-photon.npz 100%[===================>] 801.76K  --.-KB/s    in 0.01s

2021-03-19 15:06:38 (56.4 MB/s) - 'electron-photon.npz' saved [821002/821002]
```

Setting up the required libraries

In [2]:
```
!pip install -q tensorflow==2.3.1
!pip install -q tensorflow-quantum
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
```

```
     |████████████████████████████████| 320.4MB 51kB/s
     |████████████████████████████████| 460kB 20.5MB/s
     |████████████████████████████████| 20.1MB 102kB/s
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.8.3 which is incompatible.
ERROR: albumentations 0.1.12 has requirement imgaug<0.2.7,>=0.2.5, but you'll have imgaug 0.2.9 which is incompatible.
     |████████████████████████████████| 5.9MB 9.9MB/s
     |████████████████████████████████| 5.6MB 29.0MB/s
     |████████████████████████████████| 1.6MB 51.3MB/s
```

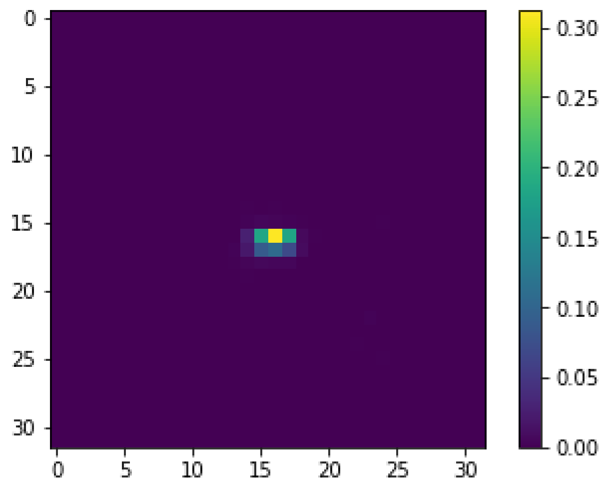
Loading the data

In [3]:
```
with np.load('./electron-photon.npz') as data:
  x_train = data['x_train']
  y_train = data['y_train']
  x_test = data['x_test']
  y_test = data['y_test']
```

In [4]:
```
# plot a sample each from the training set
print(y_train[0])

plt.imshow(x_train[0])
plt.colorbar()
```

```
1.0
```

Out[4]:
```
<matplotlib.colorbar.Colorbar at 0x7fb973b615d0>
```



Downscaling the images

An image size of 32x32 is much too large for current quantum computers. We will use PCA to downscale the images to have a feature dimension of 16 i.e., almost 99% reduction in size.

In [5]:
```
def truncate_x(x_train, x_test, n_components=10):
  """Performs PCA on image dataset keeping the top `n_components` components."""
  n_points_train = tf.gather(tf.shape(x_train), 0)
  n_points_test = tf.gather(tf.shape(x_test), 0)

  # Flatten to 1D
  x_train = tf.reshape(x_train, [n_points_train, -1])
  x_test = tf.reshape(x_test, [n_points_test, -1])

  # Normalize
  feature_mean = tf.reduce_mean(x_train, axis=0)
  x_train_normalized = x_train - feature_mean
  x_test_normalized = x_test - feature_mean

  # Truncate
  eigen_vals, eigen_vectors = tf.linalg.eigh(
      tf.einsum('ji, jk->ik', x_train_normalized, x_train_normalized))
  return tf.einsum('ij, jk->ik', x_train_normalized, eigen_vectors[:, -n_components:]), \
  tf.einsum('ij, jk->ik', x_test_normalized, eigen_vectors[:, -n_components:])
```

In [6]:
```
FEATURE_DIM = 16
x_train_small, x_test_small = truncate_x(x_train, x_test, FEATURE_DIM)
print('New Datapoint Dimension:', len(x_train_small[0]))
```

```
New Datapoint Dimension: 16
```

In [7]:
```
print(y_train[0])

print(x_train_small[0])
```

```
1.0
tf.Tensor(
[-1.6053880e-03  2.3733489e-02  1.4729184e-02 -5.9277429e-03
  3.2285508e-05  2.0039830e-02 -5.3670205e-02 -1.6176773e-02
  1.2461127e-02  3.0327177e-02  1.7056542e-02  7.0775233e-02
  3.8512979e-02 -1.3234577e-01  3.6286876e-02 -3.3949080e-01], shape=(16,), dtype=float32)
```

Encoding the data as quantum circuits

In [8]:
```
THRESHOLD = 0

x_train_bin = np.array(x_train_small > THRESHOLD, dtype=np.float32)
x_test_bin = np.array(x_test_small > THRESHOLD, dtype=np.float32)
```

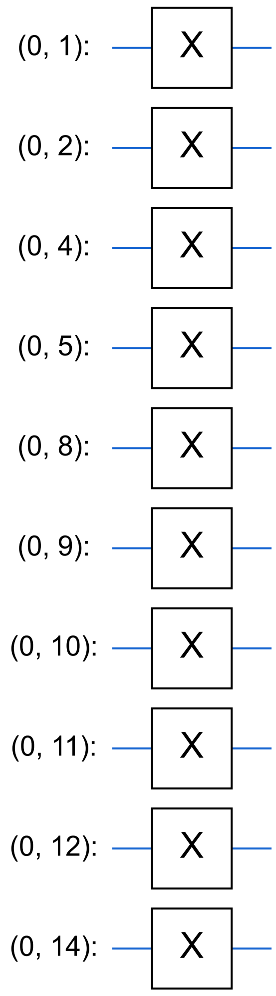
The qubits at pixel indices with values that exceed a threshold, are rotated through an X gate.

In [9]:
```
def convert_to_circuit(image):
  """Encode truncated classical image into quantum datapoint"""
  values = np.ndarray.flatten(image)
  qubits = cirq.GridQubit.rect(1, 16) # LineQubit will give an error when converting to tensors
  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_bin]
x_test_circ = [convert_to_circuit(x) for x in x_test_bin]
```

In [10]:
```
# Visualizing a sample quantum datapoint circuit
SVGCircuit(x_train_circ[0])
```

```
findfont: Font family ['Arial'] not found. Falling back to DejaVu Sans.
```

Out[10]:



In [11]:

```
# Verifying the encoding
bin_img = x_train_bin[0]
indices = np.array(np.where(bin_img)).T
indices
```

Out[11]:

```
array([[ 1],
       [ 2],
       [ 4],
       [ 5],
       [ 8],
       [ 9],
       [10],
       [11],
       [12],
       [14]])
```

Converting these Cirq circuits into tensors for TFQ

In [12]:

```
x_train_tfcirc = tfq.convert_to_tensor(x_train_circ)
x_test_tfcirc = tfq.convert_to_tensor(x_test_circ)
```

QCNN Layers

In [13]:

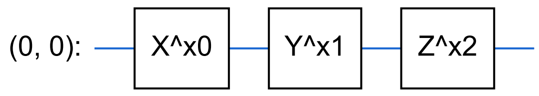
```
def one_qubit_unitary(bit, symbols):
    """Make a Cirq circuit enacting a rotation of the bloch sphere about the X,
    Y and Z axis, that depends on the values in `symbols`.
    """
    return cirq.Circuit(
        cirq.X(bit)**symbols[0],
        cirq.Y(bit)**symbols[1],
        cirq.Z(bit)**symbols[2])


def two_qubit_unitary(bits, symbols):
    """Make a Cirq circuit that creates an arbitrary two qubit unitary."""
    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):
    """Make a Cirq circuit to do a parameterized 'pooling' operation, which
    attempts to reduce entanglement down from two qubits to just one."""
    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
```

Printing circuit samples

In [14]:

```
# one qubit unitary
SVGCircuit(one_qubit_unitary(cirq.GridQubit(0, 0), sympy.symbols('x0:3')))
```

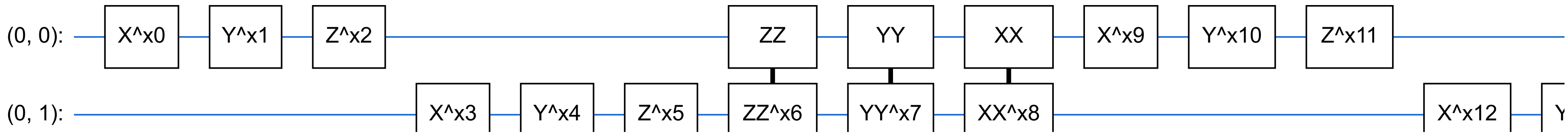
Out[14]:



In [15]:

```
# two qubit unitary
SVGCircuit(two_qubit_unitary(cirq.GridQubit.rect(1, 2), sympy.symbols('x0:15')))
```

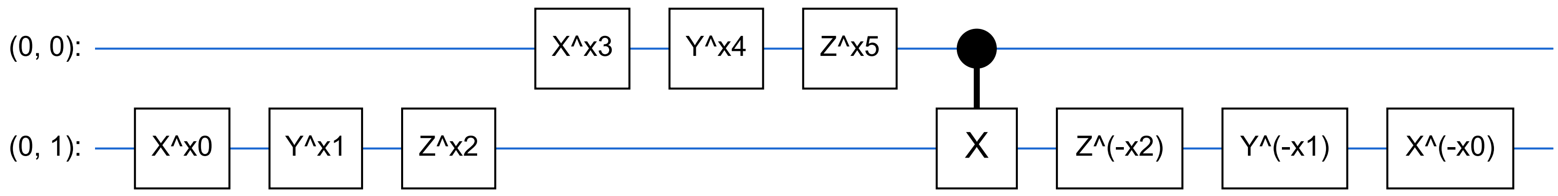
Out[15]:



In [16]:

```
# two qubit pool
SVGCircuit(two_qubit_pool(*cirq.GridQubit.rect(1, 2), sympy.symbols('x0:6')))
```

Out[16]:



Quantum Convolution

We define the 1D quantum convolution as the application of a two-qubit parameterized unitary to every pair of adjacent qubits with a stride of one.

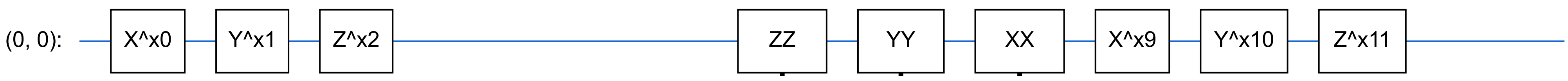
In [17]:

```
def quantum_conv_circuit(bits, symbols):
    """Quantum Convolution Layer following the above diagram.
    Return a Cirq circuit with the cascade of `two_qubit_unitary` applied
    to all pairs of qubits in `bits` as in the diagram above.
    """
    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
```

In [18]:

```
SVGCircuit(
    quantum_conv_circuit(cirq.GridQubit.rect(1, 16), sympy.symbols('x0:15')))
```

Out[18]:



Quantum pooling

A quantum pooling layer pools from N qubits to $\frac{N}{2}$ qubits using the two-qubit pool defined above.

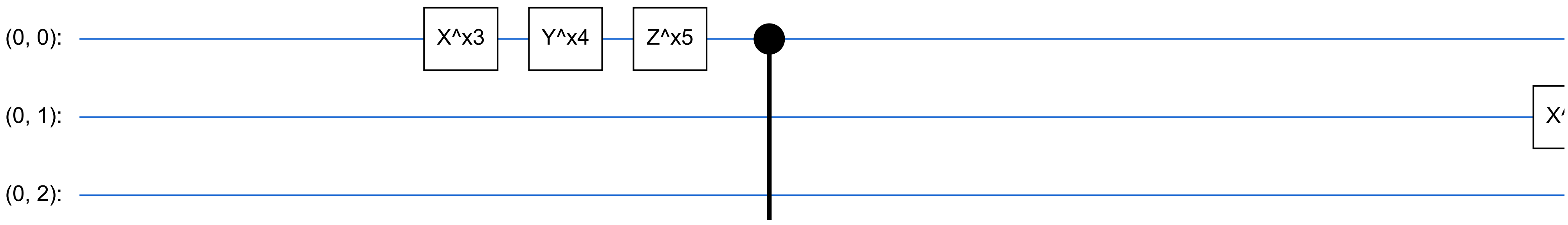
In [19]:

```
def quantum_pool_circuit(source_bits, sink_bits, symbols):
  """A layer that specifies a quantum pooling operation.
  A Quantum pool tries to learn to pool the relevant information from two
  qubits to 1.
  """
  circuit = cirq.Circuit()
  for source, sink in zip(source_bits, sink_bits):
    circuit += two_qubit_pool(source, sink, symbols)
  return circuit
```

In [20]:

```
test_bits = cirq.GridQubit.rect(1, 16)
SVGCircuit(quantum_pool_circuit(test_bits[:8], test_bits[8:], sympy.symbols('x0:6')))
```

Out[20]:



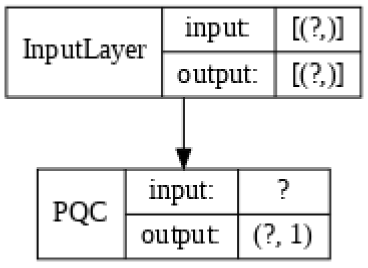
Model Definition

In [21]:

```
def create_model_circuit(qubits):
    """Create sequence of alternating convolution and pooling operators
    which gradually shrink over time."""
    model_circuit = cirq.Circuit()
    symbols = sympy.symbols('qconv0:84')
    # Cirq uses sympy.Symbols to map learnable variables. TensorFlow Quantum
    # scans incoming circuits and replaces these with TensorFlow variables.
    model_circuit += quantum_conv_circuit(qubits, symbols[0:15])
    model_circuit += quantum_pool_circuit(qubits[:8], qubits[8:],
                                          symbols[15:21])
    model_circuit += quantum_conv_circuit(qubits[8:], symbols[21:36])
    model_circuit += quantum_pool_circuit(qubits[8:12], qubits[12:],
                                          symbols[36:42])
    model_circuit += quantum_conv_circuit(qubits[12:], symbols[42:57])
    model_circuit += quantum_pool_circuit(qubits[12:14], qubits[14:],
                                          symbols[57:63])
    model_circuit += quantum_conv_circuit(qubits[14:], symbols[63:78])
```

```python
    model_circuit += quantum_pool_circuit(qubits[14:15], qubits[15:],
                                          symbols[78:84])
    # model_circuit += quantum_conv_circuit(qubits[60:], symbols[84:99])
    # model_circuit += quantum_pool_circuit(qubits[60:62], qubits[62:],
    #                                       symbols[99:105])
    # model_circuit += quantum_conv_circuit(qubits[62:], symbols[105:120])
    # model_circuit += quantum_pool_circuit(qubits[62:63], qubits[63:],
    #                                       symbols[120:126])
    return model_circuit

# Creating qubits and readout operators in Cirq
input_bits = cirq.GridQubit.rect(1, 16)
readout_operators = cirq.Z(input_bits[-1])

input_tensors = tf.keras.Input(shape=(), dtype=tf.string) # since tfq converts Cirq circuits in tf.string dtype
quantum_model = tfq.layers.PQC(create_model_circuit(input_bits), readout_operators)(input_tensors)
qcnn_model = tf.keras.Model(inputs=[input_tensors], outputs=[quantum_model])

# Show the keras plot of the model
tf.keras.utils.plot_model(qcnn_model,
                          show_shapes=True,
                          show_layer_names=False,
                          dpi=70)
```

Out[21]:



Train the model

In [22]:

```python
@tf.function
def custom_accuracy(y_true, y_pred):
    y_true = tf.squeeze(y_true)
    y_pred = tf.map_fn(lambda x: 1.0 if x >= 0 else 0.0, y_pred)
    return tf.keras.backend.mean(tf.keras.backend.equal(y_true, y_pred))

qcnn_model.compile(
    loss=tf.losses.mse,
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    metrics=[custom_accuracy])

print(qcnn_model.summary())
```

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None,)]                 0
_________________________________________________________________
pqc (PQC)                    (None, 1)                 84
=================================================================
Total params: 84
Trainable params: 84
Non-trainable params: 0
_________________________________________________________________
None
```

In [23]:

```python
EPOCHS = 100

history = qcnn_model.fit(x=x_train_tfcirc,
                         y=y_train,
                         batch_size=16,
                         epochs=EPOCHS,
                         verbose=1,
                         validation_data=(x_test_tfcirc, y_test))

qcnn_results = qcnn_model.evaluate(x_test_tfcirc, y_test)
```

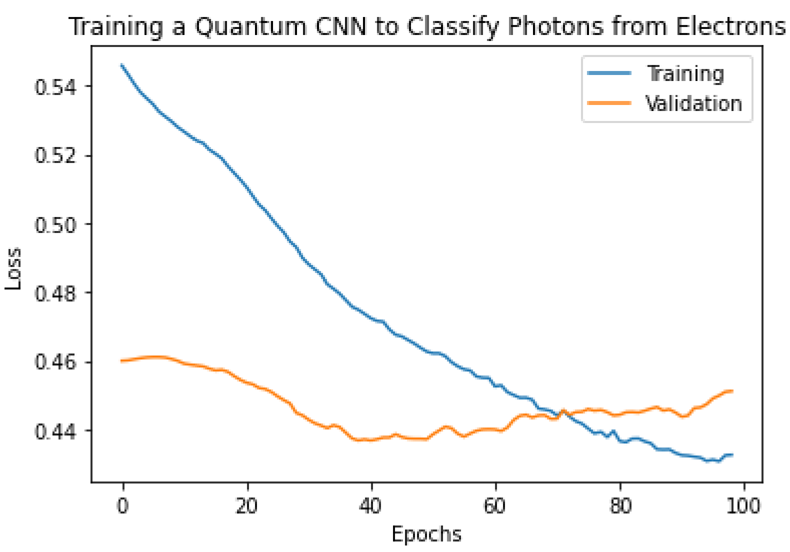
```
Epoch 1/100
7/7 [==============================] - 18s 3s/step - loss: 0.5508 - custom_accuracy: 0.4821 - val_loss: 0.4601 - val_custom_accuracy: 0.5982
Epoch 2/100
7/7 [==============================] - 18s 3s/step - loss: 0.5459 - custom_accuracy: 0.5268 - val_loss: 0.4600 - val_custom_accuracy: 0.5536
Epoch 3/100
7/7 [==============================] - 18s 3s/step - loss: 0.5433 - custom_accuracy: 0.5893 - val_loss: 0.4601 - val_custom_accuracy: 0.5536
Epoch 4/100
7/7 [==============================] - 18s 3s/step - loss: 0.5405 - custom_accuracy: 0.6071 - val_loss: 0.4604 - val_custom_accuracy: 0.5268
Epoch 5/100
7/7 [==============================] - 17s 2s/step - loss: 0.5381 - custom_accuracy: 0.6250 - val_loss: 0.4608 - val_custom_accuracy: 0.5179
Epoch 6/100
7/7 [==============================] - 17s 2s/step - loss: 0.5363 - custom_accuracy: 0.6071 - val_loss: 0.4610 - val_custom_accuracy: 0.5268
Epoch 7/100
7/7 [==============================] - 17s 2s/step - loss: 0.5346 - custom_accuracy: 0.5893 - val_loss: 0.4611 - val_custom_accuracy: 0.5089
Epoch 8/100
7/7 [==============================] - 17s 2s/step - loss: 0.5324 - custom_accuracy: 0.5804 - val_loss: 0.4611 - val_custom_accuracy: 0.5089
Epoch 9/100
7/7 [==============================] - 18s 3s/step - loss: 0.5310 - custom_accuracy: 0.5536 - val_loss: 0.4609 - val_custom_accuracy: 0.5179
Epoch 10/100
7/7 [==============================] - 18s 3s/step - loss: 0.5296 - custom_accuracy: 0.5536 - val_loss: 0.4605 - val_custom_accuracy: 0.5179
Epoch 11/100
7/7 [==============================] - 17s 2s/step - loss: 0.5279 - custom_accuracy: 0.5625 - val_loss: 0.4600 - val_custom_accuracy: 0.5179
Epoch 12/100
7/7 [==============================] - 17s 2s/step - loss: 0.5266 - custom_accuracy: 0.6696 - val_loss: 0.4592 - val_custom_accuracy: 0.5179
Epoch 13/100
```

```
7/7 [==============================] - 17s 2s/step - loss: 0.5253 - custom_accuracy: 0.6161 - val_loss: 0.4589 - val_custom_accuracy: 0.5089
Epoch 14/100
7/7 [==============================] - 17s 2s/step - loss: 0.5239 - custom_accuracy: 0.6696 - val_loss: 0.4586 - val_custom_accuracy: 0.4911
Epoch 15/100
7/7 [==============================] - 18s 3s/step - loss: 0.5233 - custom_accuracy: 0.6429 - val_loss: 0.4584 - val_custom_accuracy: 0.5089
Epoch 16/100
7/7 [==============================] - 17s 2s/step - loss: 0.5214 - custom_accuracy: 0.6607 - val_loss: 0.4577 - val_custom_accuracy: 0.5089
Epoch 17/100
7/7 [==============================] - 18s 3s/step - loss: 0.5201 - custom_accuracy: 0.6696 - val_loss: 0.4572 - val_custom_accuracy: 0.5089
Epoch 18/100
7/7 [==============================] - 17s 2s/step - loss: 0.5188 - custom_accuracy: 0.7321 - val_loss: 0.4574 - val_custom_accuracy: 0.5268
Epoch 19/100
7/7 [==============================] - 18s 3s/step - loss: 0.5165 - custom_accuracy: 0.6786 - val_loss: 0.4568 - val_custom_accuracy: 0.5357
Epoch 20/100
7/7 [==============================] - 17s 2s/step - loss: 0.5146 - custom_accuracy: 0.7321 - val_loss: 0.4555 - val_custom_accuracy: 0.5357
Epoch 21/100
7/7 [==============================] - 18s 3s/step - loss: 0.5126 - custom_accuracy: 0.6964 - val_loss: 0.4544 - val_custom_accuracy: 0.5268
Epoch 22/100
7/7 [==============================] - 17s 2s/step - loss: 0.5104 - custom_accuracy: 0.6696 - val_loss: 0.4536 - val_custom_accuracy: 0.5446
Epoch 23/100
7/7 [==============================] - 17s 2s/step - loss: 0.5079 - custom_accuracy: 0.6786 - val_loss: 0.4532 - val_custom_accuracy: 0.5357
Epoch 24/100
7/7 [==============================] - 18s 3s/step - loss: 0.5054 - custom_accuracy: 0.6607 - val_loss: 0.4521 - val_custom_accuracy: 0.5357
Epoch 25/100
7/7 [==============================] - 18s 3s/step - loss: 0.5037 - custom_accuracy: 0.6071 - val_loss: 0.4518 - val_custom_accuracy: 0.5357
Epoch 26/100
7/7 [==============================] - 18s 3s/step - loss: 0.5013 - custom_accuracy: 0.6786 - val_loss: 0.4509 - val_custom_accuracy: 0.5357
Epoch 27/100
7/7 [==============================] - 18s 3s/step - loss: 0.4991 - custom_accuracy: 0.6696 - val_loss: 0.4496 - val_custom_accuracy: 0.5446
Epoch 28/100
7/7 [==============================] - 17s 2s/step - loss: 0.4973 - custom_accuracy: 0.6875 - val_loss: 0.4485 - val_custom_accuracy: 0.5179
Epoch 29/100
7/7 [==============================] - 18s 3s/step - loss: 0.4946 - custom_accuracy: 0.6607 - val_loss: 0.4476 - val_custom_accuracy: 0.5268
Epoch 30/100
7/7 [==============================] - 18s 3s/step - loss: 0.4930 - custom_accuracy: 0.6161 - val_loss: 0.4448 - val_custom_accuracy: 0.5268
Epoch 31/100
7/7 [==============================] - 18s 3s/step - loss: 0.4898 - custom_accuracy: 0.6607 - val_loss: 0.4441 - val_custom_accuracy: 0.5446
Epoch 32/100
7/7 [==============================] - 18s 3s/step - loss: 0.4879 - custom_accuracy: 0.6607 - val_loss: 0.4428 - val_custom_accuracy: 0.5357
Epoch 33/100
7/7 [==============================] - 18s 3s/step - loss: 0.4865 - custom_accuracy: 0.5982 - val_loss: 0.4418 - val_custom_accuracy: 0.5446
Epoch 34/100
7/7 [==============================] - 17s 2s/step - loss: 0.4850 - custom_accuracy: 0.6161 - val_loss: 0.4411 - val_custom_accuracy: 0.5357
Epoch 35/100
7/7 [==============================] - 17s 2s/step - loss: 0.4823 - custom_accuracy: 0.6607 - val_loss: 0.4404 - val_custom_accuracy: 0.5536
Epoch 36/100
7/7 [==============================] - 17s 2s/step - loss: 0.4810 - custom_accuracy: 0.6607 - val_loss: 0.4412 - val_custom_accuracy: 0.5446
Epoch 37/100
7/7 [==============================] - 17s 2s/step - loss: 0.4795 - custom_accuracy: 0.6518 - val_loss: 0.4407 - val_custom_accuracy: 0.5446
Epoch 38/100
7/7 [==============================] - 18s 3s/step - loss: 0.4776 - custom_accuracy: 0.6250 - val_loss: 0.4390 - val_custom_accuracy: 0.5536
Epoch 39/100
7/7 [==============================] - 18s 3s/step - loss: 0.4757 - custom_accuracy: 0.6071 - val_loss: 0.4374 - val_custom_accuracy: 0.5625
Epoch 40/100
7/7 [==============================] - 17s 2s/step - loss: 0.4749 - custom_accuracy: 0.5625 - val_loss: 0.4368 - val_custom_accuracy: 0.5536
Epoch 41/100
7/7 [==============================] - 17s 2s/step - loss: 0.4736 - custom_accuracy: 0.6696 - val_loss: 0.4371 - val_custom_accuracy: 0.5714
Epoch 42/100
7/7 [==============================] - 18s 3s/step - loss: 0.4724 - custom_accuracy: 0.5893 - val_loss: 0.4368 - val_custom_accuracy: 0.5625
Epoch 43/100
7/7 [==============================] - 17s 2s/step - loss: 0.4716 - custom_accuracy: 0.6429 - val_loss: 0.4371 - val_custom_accuracy: 0.5625
Epoch 44/100
7/7 [==============================] - 17s 2s/step - loss: 0.4714 - custom_accuracy: 0.6696 - val_loss: 0.4376 - val_custom_accuracy: 0.5536
Epoch 45/100
7/7 [==============================] - 17s 2s/step - loss: 0.4691 - custom_accuracy: 0.5893 - val_loss: 0.4377 - val_custom_accuracy: 0.5357
Epoch 46/100
7/7 [==============================] - 17s 2s/step - loss: 0.4676 - custom_accuracy: 0.6071 - val_loss: 0.4386 - val_custom_accuracy: 0.5536
Epoch 47/100
7/7 [==============================] - 18s 3s/step - loss: 0.4671 - custom_accuracy: 0.6607 - val_loss: 0.4378 - val_custom_accuracy: 0.5536
Epoch 48/100
7/7 [==============================] - 17s 2s/step - loss: 0.4660 - custom_accuracy: 0.5804 - val_loss: 0.4374 - val_custom_accuracy: 0.5446
Epoch 49/100
7/7 [==============================] - 18s 3s/step - loss: 0.4650 - custom_accuracy: 0.5804 - val_loss: 0.4373 - val_custom_accuracy: 0.5625
Epoch 50/100
7/7 [==============================] - 18s 3s/step - loss: 0.4638 - custom_accuracy: 0.6071 - val_loss: 0.4373 - val_custom_accuracy: 0.5536
Epoch 51/100
7/7 [==============================] - 17s 2s/step - loss: 0.4627 - custom_accuracy: 0.6071 - val_loss: 0.4371 - val_custom_accuracy: 0.5714
Epoch 52/100
7/7 [==============================] - 17s 2s/step - loss: 0.4622 - custom_accuracy: 0.6250 - val_loss: 0.4386 - val_custom_accuracy: 0.5804
Epoch 53/100
7/7 [==============================] - 17s 2s/step - loss: 0.4622 - custom_accuracy: 0.5625 - val_loss: 0.4397 - val_custom_accuracy: 0.5625
Epoch 54/100
7/7 [==============================] - 18s 3s/step - loss: 0.4613 - custom_accuracy: 0.5982 - val_loss: 0.4408 - val_custom_accuracy: 0.5804
Epoch 55/100
7/7 [==============================] - 18s 3s/step - loss: 0.4596 - custom_accuracy: 0.5982 - val_loss: 0.4404 - val_custom_accuracy: 0.5804
Epoch 56/100
7/7 [==============================] - 18s 3s/step - loss: 0.4584 - custom_accuracy: 0.5625 - val_loss: 0.4387 - val_custom_accuracy: 0.5625
Epoch 57/100
7/7 [==============================] - 18s 3s/step - loss: 0.4575 - custom_accuracy: 0.5982 - val_loss: 0.4379 - val_custom_accuracy: 0.5625
Epoch 58/100
7/7 [==============================] - 18s 3s/step - loss: 0.4572 - custom_accuracy: 0.5714 - val_loss: 0.4388 - val_custom_accuracy: 0.5625
Epoch 59/100
7/7 [==============================] - 19s 3s/step - loss: 0.4554 - custom_accuracy: 0.6071 - val_loss: 0.4396 - val_custom_accuracy: 0.5536
Epoch 60/100
7/7 [==============================] - 18s 3s/step - loss: 0.4551 - custom_accuracy: 0.5893 - val_loss: 0.4400 - val_custom_accuracy: 0.5714
Epoch 61/100
7/7 [==============================] - 18s 3s/step - loss: 0.4550 - custom_accuracy: 0.5714 - val_loss: 0.4401 - val_custom_accuracy: 0.5804
Epoch 62/100
7/7 [==============================] - 18s 3s/step - loss: 0.4525 - custom_accuracy: 0.6339 - val_loss: 0.4400 - val_custom_accuracy: 0.5804
Epoch 63/100
7/7 [==============================] - 18s 3s/step - loss: 0.4528 - custom_accuracy: 0.5625 - val_loss: 0.4395 - val_custom_accuracy: 0.5893
Epoch 64/100
7/7 [==============================] - 18s 3s/step - loss: 0.4509 - custom_accuracy: 0.5625 - val_loss: 0.4406 - val_custom_accuracy: 0.5625
```

```
Epoch 65/100
7/7 [==============================] - 18s 3s/step - loss: 0.4500 - custom_accuracy: 0.5804 - val_loss: 0.4427 - val_custom_accuracy: 0.5625
Epoch 66/100
7/7 [==============================] - 18s 3s/step - loss: 0.4492 - custom_accuracy: 0.5982 - val_loss: 0.4440 - val_custom_accuracy: 0.5446
Epoch 67/100
7/7 [==============================] - 18s 3s/step - loss: 0.4492 - custom_accuracy: 0.6607 - val_loss: 0.4443 - val_custom_accuracy: 0.5625
Epoch 68/100
7/7 [==============================] - 18s 3s/step - loss: 0.4486 - custom_accuracy: 0.6250 - val_loss: 0.4435 - val_custom_accuracy: 0.5536
Epoch 69/100
7/7 [==============================] - 18s 3s/step - loss: 0.4461 - custom_accuracy: 0.6071 - val_loss: 0.4441 - val_custom_accuracy: 0.5536
Epoch 70/100
7/7 [==============================] - 18s 3s/step - loss: 0.4458 - custom_accuracy: 0.5982 - val_loss: 0.4442 - val_custom_accuracy: 0.5804
Epoch 71/100
7/7 [==============================] - 18s 3s/step - loss: 0.4454 - custom_accuracy: 0.5982 - val_loss: 0.4431 - val_custom_accuracy: 0.5893
Epoch 72/100
7/7 [==============================] - 18s 3s/step - loss: 0.4441 - custom_accuracy: 0.6250 - val_loss: 0.4431 - val_custom_accuracy: 0.5893
Epoch 73/100
7/7 [==============================] - 18s 3s/step - loss: 0.4454 - custom_accuracy: 0.6250 - val_loss: 0.4456 - val_custom_accuracy: 0.5446
Epoch 74/100
7/7 [==============================] - 18s 3s/step - loss: 0.4437 - custom_accuracy: 0.6250 - val_loss: 0.4442 - val_custom_accuracy: 0.5357
Epoch 75/100
7/7 [==============================] - 18s 3s/step - loss: 0.4424 - custom_accuracy: 0.5893 - val_loss: 0.4450 - val_custom_accuracy: 0.5446
Epoch 76/100
7/7 [==============================] - 18s 3s/step - loss: 0.4417 - custom_accuracy: 0.5268 - val_loss: 0.4451 - val_custom_accuracy: 0.5804
Epoch 77/100
7/7 [==============================] - 17s 2s/step - loss: 0.4402 - custom_accuracy: 0.6071 - val_loss: 0.4459 - val_custom_accuracy: 0.5714
Epoch 78/100
7/7 [==============================] - 17s 2s/step - loss: 0.4388 - custom_accuracy: 0.6250 - val_loss: 0.4455 - val_custom_accuracy: 0.5804
Epoch 79/100
7/7 [==============================] - 17s 2s/step - loss: 0.4393 - custom_accuracy: 0.6339 - val_loss: 0.4457 - val_custom_accuracy: 0.5893
Epoch 80/100
7/7 [==============================] - 17s 2s/step - loss: 0.4378 - custom_accuracy: 0.6429 - val_loss: 0.4450 - val_custom_accuracy: 0.6071
Epoch 81/100
7/7 [==============================] - 17s 2s/step - loss: 0.4396 - custom_accuracy: 0.6518 - val_loss: 0.4441 - val_custom_accuracy: 0.5804
Epoch 82/100
7/7 [==============================] - 17s 2s/step - loss: 0.4366 - custom_accuracy: 0.6339 - val_loss: 0.4443 - val_custom_accuracy: 0.5804
Epoch 83/100
7/7 [==============================] - 17s 2s/step - loss: 0.4363 - custom_accuracy: 0.6161 - val_loss: 0.4450 - val_custom_accuracy: 0.5893
Epoch 84/100
7/7 [==============================] - 17s 2s/step - loss: 0.4373 - custom_accuracy: 0.6429 - val_loss: 0.4451 - val_custom_accuracy: 0.5982
Epoch 85/100
7/7 [==============================] - 17s 2s/step - loss: 0.4374 - custom_accuracy: 0.6339 - val_loss: 0.4449 - val_custom_accuracy: 0.5893
Epoch 86/100
7/7 [==============================] - 17s 2s/step - loss: 0.4365 - custom_accuracy: 0.6518 - val_loss: 0.4454 - val_custom_accuracy: 0.5714
Epoch 87/100
7/7 [==============================] - 17s 2s/step - loss: 0.4360 - custom_accuracy: 0.6339 - val_loss: 0.4460 - val_custom_accuracy: 0.5625
Epoch 88/100
7/7 [==============================] - 17s 2s/step - loss: 0.4342 - custom_accuracy: 0.6875 - val_loss: 0.4465 - val_custom_accuracy: 0.5714
Epoch 89/100
7/7 [==============================] - 17s 2s/step - loss: 0.4341 - custom_accuracy: 0.6607 - val_loss: 0.4455 - val_custom_accuracy: 0.5893
Epoch 90/100
7/7 [==============================] - 17s 2s/step - loss: 0.4342 - custom_accuracy: 0.6607 - val_loss: 0.4458 - val_custom_accuracy: 0.6161
Epoch 91/100
7/7 [==============================] - 17s 2s/step - loss: 0.4331 - custom_accuracy: 0.6607 - val_loss: 0.4449 - val_custom_accuracy: 0.5625
Epoch 92/100
7/7 [==============================] - 17s 2s/step - loss: 0.4325 - custom_accuracy: 0.6607 - val_loss: 0.4437 - val_custom_accuracy: 0.5625
Epoch 93/100
7/7 [==============================] - 17s 2s/step - loss: 0.4324 - custom_accuracy: 0.6518 - val_loss: 0.4441 - val_custom_accuracy: 0.5536
Epoch 94/100
7/7 [==============================] - 17s 2s/step - loss: 0.4320 - custom_accuracy: 0.6518 - val_loss: 0.4462 - val_custom_accuracy: 0.6071
Epoch 95/100
7/7 [==============================] - 17s 2s/step - loss: 0.4318 - custom_accuracy: 0.6518 - val_loss: 0.4464 - val_custom_accuracy: 0.5536
Epoch 96/100
7/7 [==============================] - 17s 2s/step - loss: 0.4308 - custom_accuracy: 0.6250 - val_loss: 0.4473 - val_custom_accuracy: 0.5536
Epoch 97/100
7/7 [==============================] - 17s 2s/step - loss: 0.4312 - custom_accuracy: 0.6429 - val_loss: 0.4490 - val_custom_accuracy: 0.5446
Epoch 98/100
7/7 [==============================] - 17s 2s/step - loss: 0.4307 - custom_accuracy: 0.6518 - val_loss: 0.4499 - val_custom_accuracy: 0.5446
Epoch 99/100
7/7 [==============================] - 18s 3s/step - loss: 0.4325 - custom_accuracy: 0.6250 - val_loss: 0.4510 - val_custom_accuracy: 0.5536
Epoch 100/100
7/7 [==============================] - 18s 3s/step - loss: 0.4326 - custom_accuracy: 0.6339 - val_loss: 0.4512 - val_custom_accuracy: 0.5536
4/4 [==============================] - 1s 169ms/step - loss: 0.4512 - custom_accuracy: 0.5469
```

In [24]:

```python
plt.plot(history.history['loss'][1:], label='Training')
plt.plot(history.history['val_loss'][1:], label='Validation')
plt.title('Training a Quantum CNN to Classify Photons from Electrons')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [25]:
```
plt.plot(history.history['custom_accuracy'][1:], label='Training')
plt.plot(history.history['val_custom_accuracy'][1:], label='Validation')
plt.title('Training a Quantum CNN to Classify Photons from Electrons')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```