Appendix

A. Training Notebook

This notebook contains the code for training the model on the MNIST dataset, evaluation can be found at test.ipynb

1) Imports: For training the model, we need only tensorflow and tensorflow_datasets, which will be used to retrieve the MNIST dataset

[1]:
```
import matplotlib.pyplot as plt
import tensorflow as tf
import tensorflow_datasets as tfds
import numpy as np
from sklearn.model_selection import train_test_split
import itertools
from copy import deepcopy
```

2) Loading the dataset: We use the load method to load the mnist dataset

[2]:
```
# Import the dataset mnist is 60k images of 28x28 pixels
# And 10k images for testing
(dstrain, dstest), dsinfo = tfds.load(
    'mnist',
    split=['train', 'test'],
    data_dir='../dataset/',
    shuffle_files=True,
    as_supervised=True,
    with_info=True,
)
```

```
2022-04-30 22:43:22.101616: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.128722: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.128874: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.156073: I tensorflow/core/platform/cpu_feature_guard.cc:
↪151]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2022-04-30 22:43:22.156488: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.156655: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.156760: I
```

```
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.545077: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.545234: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.545350: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:936] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2022-04-30 22:43:22.545445: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:1525] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 4793 MB memory:  -> device:␣
↪0,
name: NVIDIA GeForce GTX 1060 6GB, pci bus id: 0000:01:00.0, compute␣
↪capability:
6.1
```

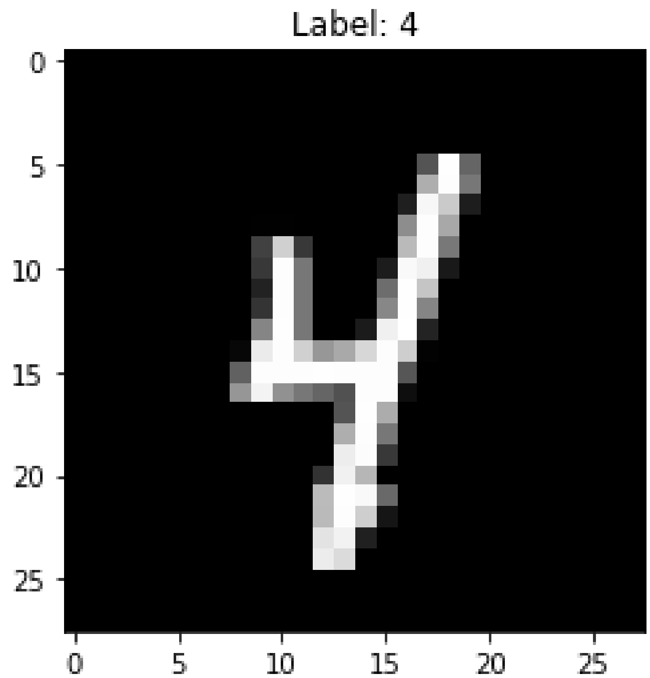
Print the image shape and class names

[3]:
```python
# Summarize loaded datasets
print('\nDataset info:')
print('Image shape:')
print(dsinfo.features['image'].shape)
print('Class Names')
print(dsinfo.features['label'].names)
```

```
Dataset info:
Image shape:
(28, 28, 1)
Class Names
['0', '1', '2', '3', '4', '5', '6', '7', '8', '9']
```

Visualize an image from the dataset

[4]:
```python
# Visualize a single image
def visualize_image(image, label):
    plt.imshow(image, cmap='gray')
    plt.title('Label: {}'.format(label))
    plt.show()


# Now use that function
mnist_example = dstrain.take(1)
for sample in mnist_example:
    image, label = sample[0], sample[1]
    visualize_image(image, label)
    break
```




```
2022-04-30 22:43:28.205713: W
tensorflow/core/kernels/data/cache_dataset_ops.cc:768] The calling iterator
↪did
not fully read the dataset being cached. In order to avoid unexpected
↪truncation
of the dataset, the partially cached contents of the dataset  will be
↪discarded.
This can happen if you have an input pipeline similar to
`dataset.cache().take(k).repeat()`. You should use
`dataset.take(k).cache().repeat()` instead.
```

Note that these wont be used, and that the dataset will be loaded multiple times with different splits in the experimentation

3) Data pipeline: No preprocessing to the image data is going to be done, raw data is going to be inputted to the model directly, the data pipeline is only going to consist of batching the data into 128 images per batch, and applying an autotuned prefetch to make the fetching of the data faster

Note: instead of preprocessing the data right now, we have a resizing layer in the model architecture

From the Tensorflow Documentation: > Prefetching overlaps the preprocessing and model execution of a training step. While the model is executing training step `s`, the input pipeline is reading the data for step `s+1`. Doing so reduces the step time to the maximum (as opposed to the sum) of the training and the time it takes to extract the data.

[5]:
```python
def trainpreprocess(dstrain, split, batch_size=128):

    dstrain = dstrain.batch(batch_size)
    dstrain = dstrain.cache()
    dstrain = dstrain.shuffle(dsinfo.splits['train+test[:' + split + ']'].
↪num_examples)
```

```
    dstrain = dstrain.prefetch(tf.data.AUTOTUNE)
    return dstrain
```

We do the same for the testing set

[6]:
```
def testpreprocess(dstest, batch_size=128):
    dstest = dstest.batch(batch_size)
    dstest = dstest.cache()
    dstest = dstest.prefetch(tf.data.AUTOTUNE)
    return dstest
```

4) The Model: We then create the model architecture

[7]:
```
def make_model(a):
    model = tf.keras.Sequential([
        tf.keras.layers.Rescaling(1./255, input_shape=(28, 28, 1)),
        tf.keras.layers.Conv2D(28, (3, 3), activation='relu'),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Conv2D(28, (3, 3), activation='relu'),
        tf.keras.layers.MaxPooling2D(2, 2),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(a[0], activation='relu'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dense(a[1], activation='relu'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dense(a[2], activation='relu'),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dense(10, activation='softmax')
    ])
    return model
```

We do the experimentation using the adam optimizer, which is a version of stochastic gradient descent, and cross categorical cross entropy for the loss function which is mathematically written as:

$$J(\mathbf{w}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

We then build the model, and test it, saving along the way the accuracy value

[ ]:
```
splits = ['60%', '70%', '80%']
hiddenlayerneurons = [p for p in itertools.product([60, 80, 100], repeat =␣
 ↪3)] # all perumations of 60, 80, 100, so (60,60,60), (60, 60, 80), ....␣
 ↪,(100, 100, 100)
i = 1
best_accuracy = 0
best_split = 0
best_neuron_counts = 0
best_iter = 1
accuracy = tf.keras.metrics.Accuracy()
allacc = []
model = None
for each_split in splits:
    for each_neuron_counts in hiddenlayerneurons:
        model_name = 'model_' + str(i)
```

```
        (dstrain, dstest), dsinfo = tfds.load(
            'mnist',
            split=['train+test[:' + each_split + ']', 'train+test[' +␣
↪each_split + ':]'],
            data_dir='../dataset/',
            shuffle_files=True,
            as_supervised=True,
            with_info=True,
        )
        dstrain = trainpreprocess(dstrain, each_split)
        dstest = testpreprocess(dstest)
        model = make_model(each_neuron_counts)
        model.compile(
            optimizer='adam',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy']
        )
        model.build()
        history = model.fit(
            dstrain,
            epochs=30,
            validation_data=dstest,
            callbacks=[
                tf.keras.callbacks.EarlyStopping(
                    monitor='val_loss',
                    patience=3
                    ,
                ),
                tf.keras.callbacks.ModelCheckpoint(
                    model_name + '.h5',
                    monitor='val_loss',
                    save_best_only=True,
                    verbose=1)
            ]
        )
        model = tf.keras.models.load_model('./' + model_name + '.h5')
        model_predictions = model.predict(dstest)
        predicted_labels = [np.argmax(x) for x in model_predictions]
        true_labels = np.concatenate([y for x, y in dstest], axis=0)
        # print(true_labels[:-10])
        # print(predicted_labels[:-10])
        accuracy.update_state(y_true = true_labels, y_pred =␣
↪predicted_labels)
        curracc = accuracy.result().numpy()
        allacc.append({'test_split' : each_split, 'neuron_counts' :␣
↪each_neuron_counts, 'accuracy' : curracc})
        print(allacc[-1])
        if(curracc > best_accuracy):
            best_accuracy = curracc
            best_split = each_split
            best_neuron_counts = each_neuron_counts
            best_iter = deepcopy(i)
        accuracy.reset_state()
```

```
        i += 1
print("best accuracy = {best_accuracy}, best split = {best_split}, best␣
↪neuron counts = {best_neuron_counts}")
```

Save the table to a csv

[23]:
```
import csv
keys = allacc[0].keys()
with open('models.csv', 'w', newline='') as output_file:
    dict_writer = csv.DictWriter(output_file, keys)
    dict_writer.writeheader()
    dict_writer.writerows(allacc)
```

Load the best model and print its summary

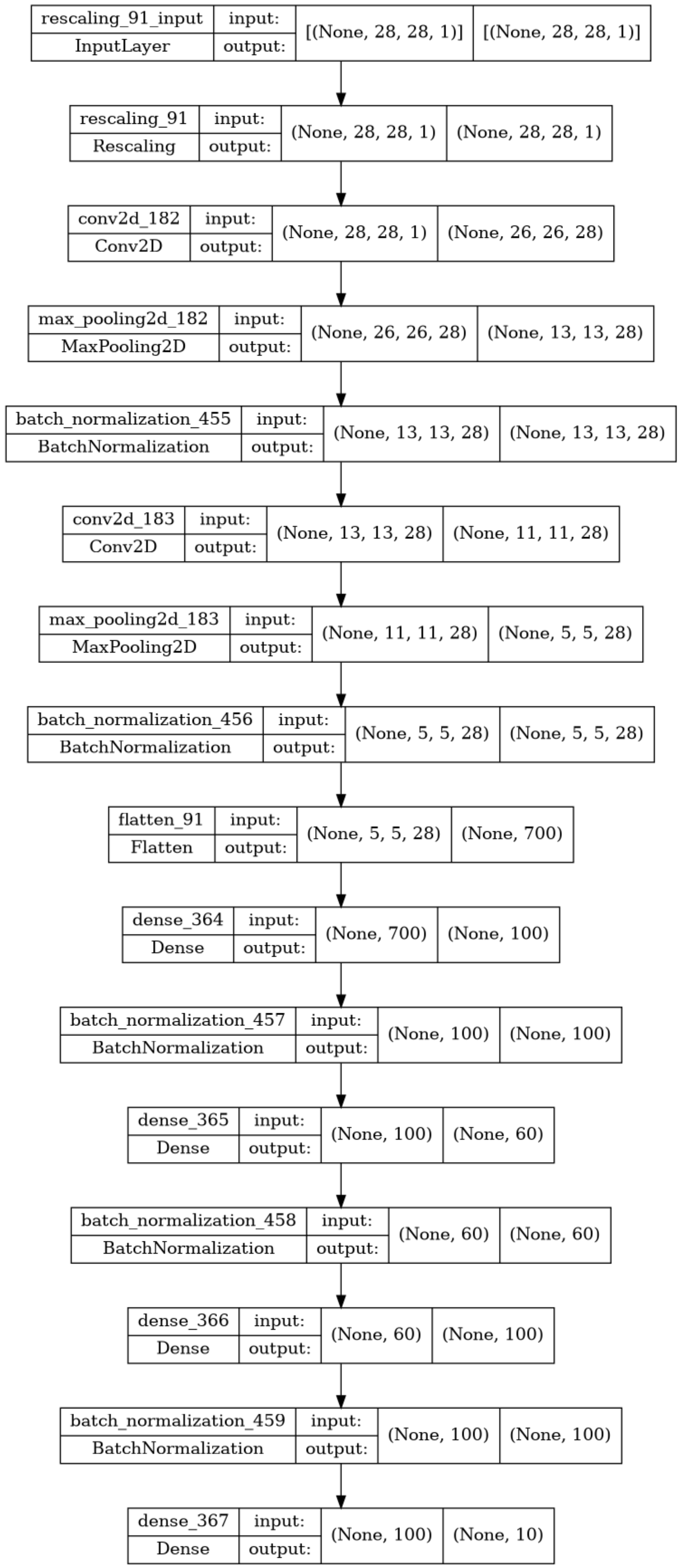
[24]:
```
model = tf.keras.models.load_model('./model_' + str(best_iter) + '.h5')
model.summary()
```

```
Model: "sequential_91"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_91 (Rescaling)    (None, 28, 28, 1)         0

 conv2d_182 (Conv2D)         (None, 26, 26, 28)        280

 max_pooling2d_182 (MaxPooli  (None, 13, 13, 28)       0
 ng2D)

 batch_normalization_455 (Ba  (None, 13, 13, 28)       112
 tchNormalization)

 conv2d_183 (Conv2D)         (None, 11, 11, 28)        7084

 max_pooling2d_183 (MaxPooli  (None, 5, 5, 28)         0
 ng2D)

 batch_normalization_456 (Ba  (None, 5, 5, 28)         112
 tchNormalization)

 flatten_91 (Flatten)        (None, 700)               0

 dense_364 (Dense)           (None, 100)               70100

 batch_normalization_457 (Ba  (None, 100)              400
 tchNormalization)

 dense_365 (Dense)           (None, 60)                6060

 batch_normalization_458 (Ba  (None, 60)               240
 tchNormalization)

 dense_366 (Dense)           (None, 100)               6100
```

```
 batch_normalization_459 (Ba  (None, 100)              400
 tchNormalization)

 dense_367 (Dense)           (None, 10)                1010

=================================================================
Total params: 91,898
Trainable params: 91,266
Non-trainable params: 632
_________________________________________________________________
```

Create the architecture diagram and save it to an svg

[25]:
```
import pydot
from IPython.display import Image, display

def view_pydot(pdot):
    plt = Image(pdot.create_png())
    display(plt)


architecture = tf.keras.utils.model_to_dot(model, show_shapes = True)
view_pydot(architecture)
architecture.write_svg('../paper/figs/cnn_architecture.svg')
```

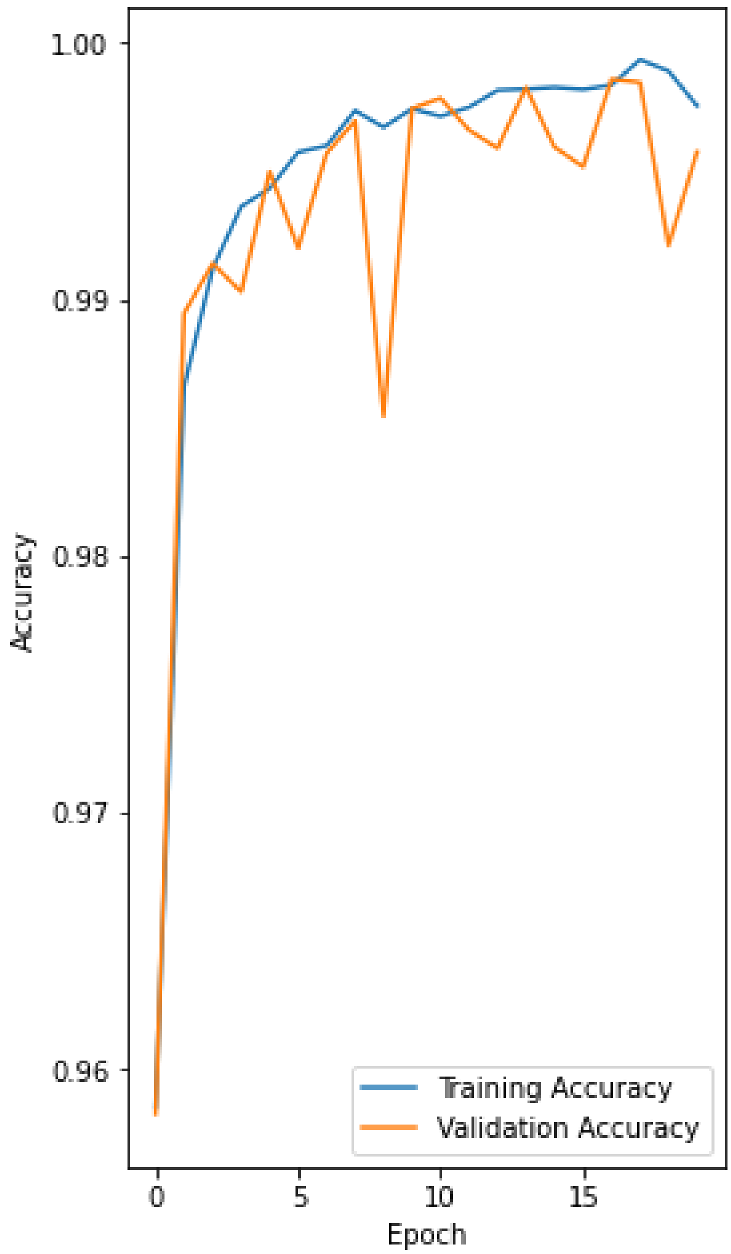

rescaling_91_input | InputLayer | input: [(None, 28, 28, 1)] | output: [(None, 28, 28, 1)]
rescaling_91 | Rescaling | input: (None, 28, 28, 1) | output: (None, 28, 28, 1)
conv2d_182 | Conv2D | input: (None, 28, 28, 1) | output: (None, 26, 26, 28)
max_pooling2d_182 | MaxPooling2D | input: (None, 26, 26, 28) | output: (None, 13, 13, 28)
batch_normalization_455 | BatchNormalization | input: (None, 13, 13, 28) | output: (None, 13, 13, 28)
conv2d_183 | Conv2D | input: (None, 13, 13, 28) | output: (None, 11, 11, 28)
max_pooling2d_183 | MaxPooling2D | input: (None, 11, 11, 28) | output: (None, 5, 5, 28)
batch_normalization_456 | BatchNormalization | input: (None, 5, 5, 28) | output: (None, 5, 5, 28)
flatten_91 | Flatten | input: (None, 5, 5, 28) | output: (None, 700)
dense_364 | Dense | input: (None, 700) | output: (None, 100)
batch_normalization_457 | BatchNormalization | input: (None, 100) | output: (None, 100)
dense_365 | Dense | input: (None, 100) | output: (None, 60)
batch_normalization_458 | BatchNormalization | input: (None, 60) | output: (None, 60)
dense_366 | Dense | input: (None, 60) | output: (None, 100)
batch_normalization_459 | BatchNormalization | input: (None, 100) | output: (None, 100)
dense_367 | Dense | input: (None, 100) | output: (None, 10)

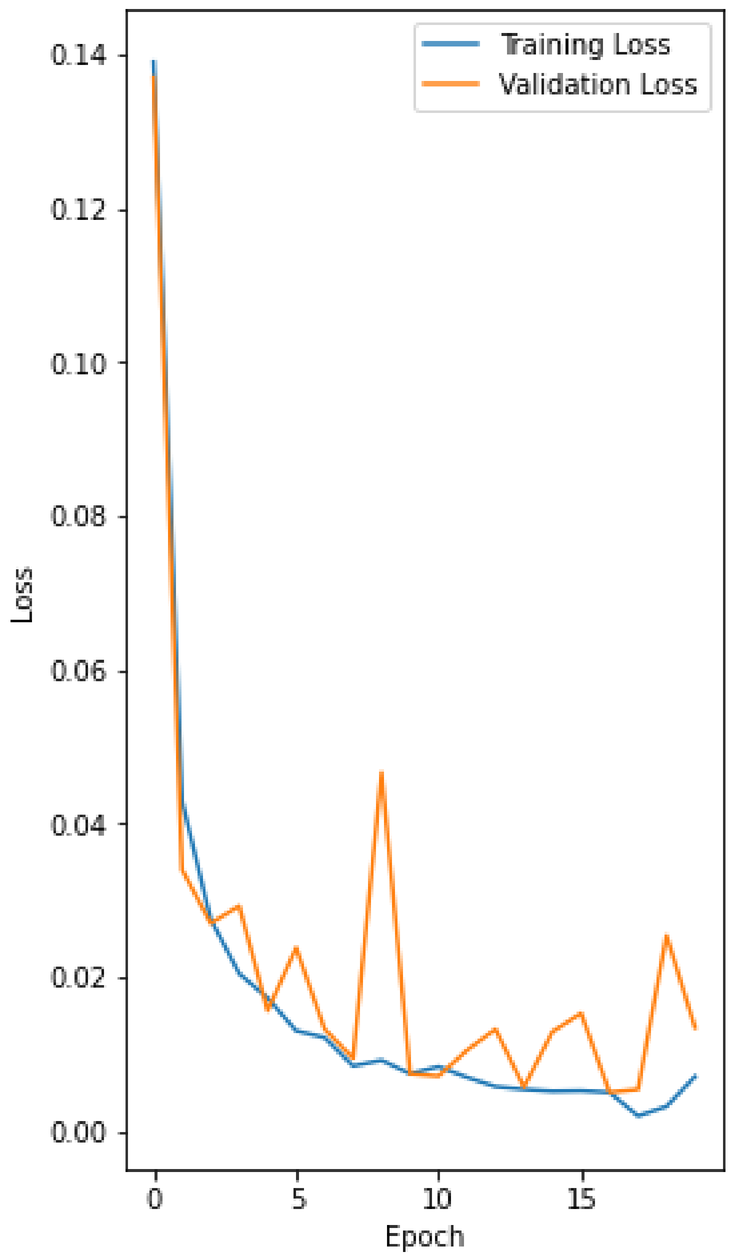
Save the model to `model.h5` so that we can load it again in the test script

```
[26]: model.save('./model.h5')
```

Plot the accuracies and the losses across the range of epochs

```
[27]: accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(len(accuracy))

plt.figure(figsize=(4, 8))
plt.plot(epochs_range, accuracy, label='Training Accuracy')
plt.plot(epochs_range, val_accuracy, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.savefig('../paper/figs/accuracy.svg', format='svg')
plt.show()

plt.figure(figsize=(4, 8))
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.savefig('../paper/figs/loss.svg', format='svg')
plt.show()
```


1.00
0.99
0.98
0.97
0.96
Accuracy
0
5
10
15
Epoch
Training Accuracy
Validation Accuracy


Training Loss
Validation Loss
Loss
Epoch
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0
5
10
15