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
```

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

[ ]:
```
# 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,
)
```

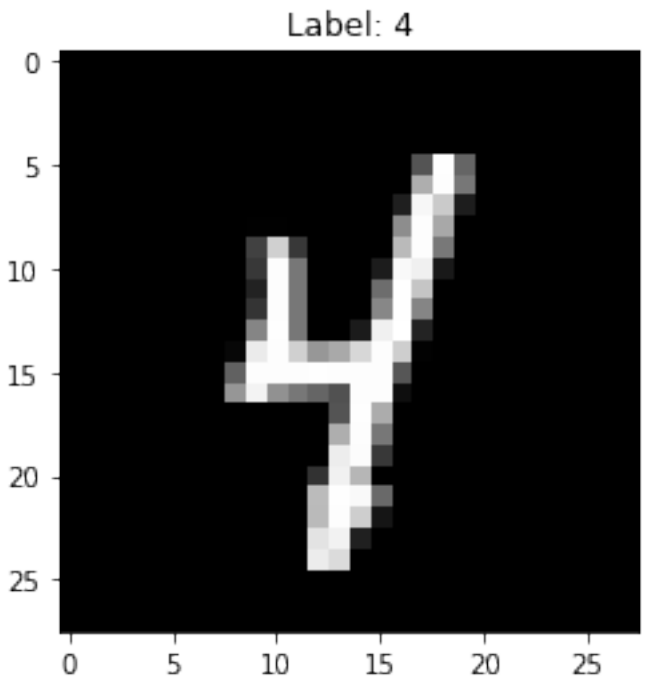
Print the image shape and class names

[3]:
```
# 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]:
```
# 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
```




```
2022-04-24 22:37:42.374927: 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.
```

3) Preprocessing: We preprocess the data by batching it, 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]:
```
batch_size = 128

dstrain = dstrain.batch(batch_size)
dstrain = dstrain.cache()
dstrain = dstrain.shuffle(dsinfo.splits['train'].num_examples)
dstrain = dstrain.prefetch(tf.data.AUTOTUNE)
```

We do the same for the testing set

[6]:
```
dstest = dstest.batch(batch_size)
dstest = dstest.cache()
dstest = dstest.prefetch(tf.data.AUTOTUNE)
```

4) The Model: We then create the model architecture

[7]:
```
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(128, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
])
```

We compile the model, where we use 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 print the summary

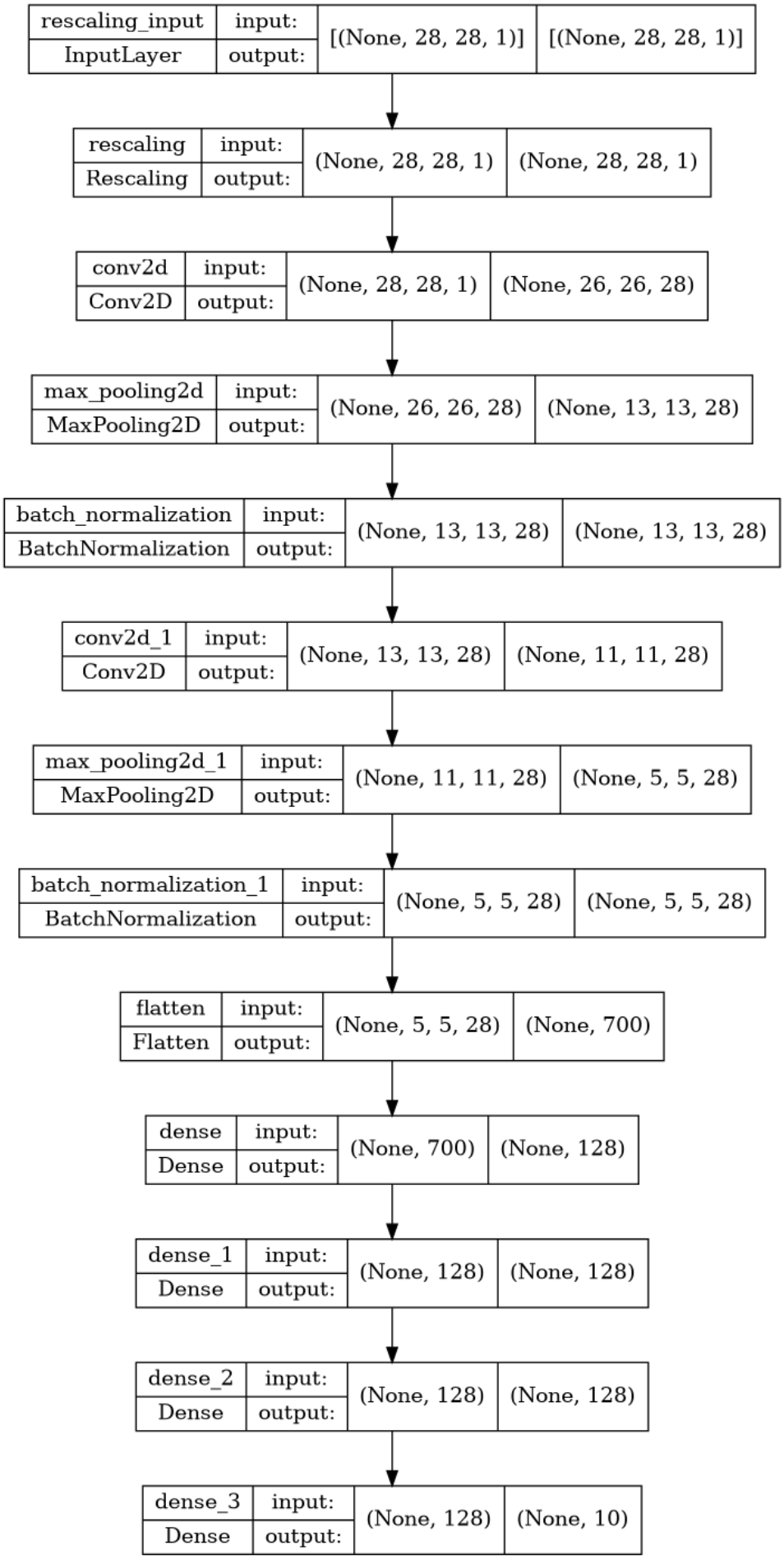
[8]:
```
model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy'],
)

# build the model
model.build()
# print the model summary
model.summary()
```

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

 conv2d (Conv2D)             (None, 26, 26, 28)        280

 max_pooling2d (MaxPooling2D  (None, 13, 13, 28)       0
 )

 batch_normalization (BatchN  (None, 13, 13, 28)       112
 ormalization)

 conv2d_1 (Conv2D)           (None, 11, 11, 28)        7084
```

```
max_pooling2d_1 (MaxPooling  (None, 5, 5, 28)         0
2D)

batch_normalization_1 (Batc  (None, 5, 5, 28)         112
hNormalization)

flatten (Flatten)            (None, 700)              0

dense (Dense)                (None, 128)              89728

dense_1 (Dense)              (None, 128)              16512

dense_2 (Dense)              (None, 128)              16512

dense_3 (Dense)              (None, 10)               1290

=================================================================
Total params: 131,630
Trainable params: 131,518
Non-trainable params: 112
_________________________________________________________________
```

Create the architecture diagram and save it to an svg

[9]:
```
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_input
InputLayer
input:
output:
[(None, 28, 28, 1)]
[(None, 28, 28, 1)]
rescaling
Rescaling
input:
output:
(None, 28, 28, 1)
(None, 28, 28, 1)
conv2d
Conv2D
input:
output:
(None, 28, 28, 1)
(None, 26, 26, 28)
max_pooling2d
MaxPooling2D
input:
output:
(None, 26, 26, 28)
(None, 13, 13, 28)
batch_normalization
BatchNormalization
input:
output:
(None, 13, 13, 28)
(None, 13, 13, 28)
conv2d_1
Conv2D
input:
output:
(None, 13, 13, 28)
(None, 11, 11, 28)
max_pooling2d_1
MaxPooling2D
input:
output:
(None, 11, 11, 28)
(None, 5, 5, 28)
batch_normalization_1
BatchNormalization
input:
output:
(None, 5, 5, 28)
(None, 5, 5, 28)
flatten
Flatten
input:
output:
(None, 5, 5, 28)
(None, 700)
dense
Dense
input:
output:
(None, 700)
(None, 128)
dense_1
Dense
input:
output:
(None, 128)
(None, 128)
dense_2
Dense
input:
output:
(None, 128)
(None, 128)
dense_3
Dense
input:
output:
(None, 128)
(None, 10)

We them train the model, with an early stopping callback, and saving the best model along the way

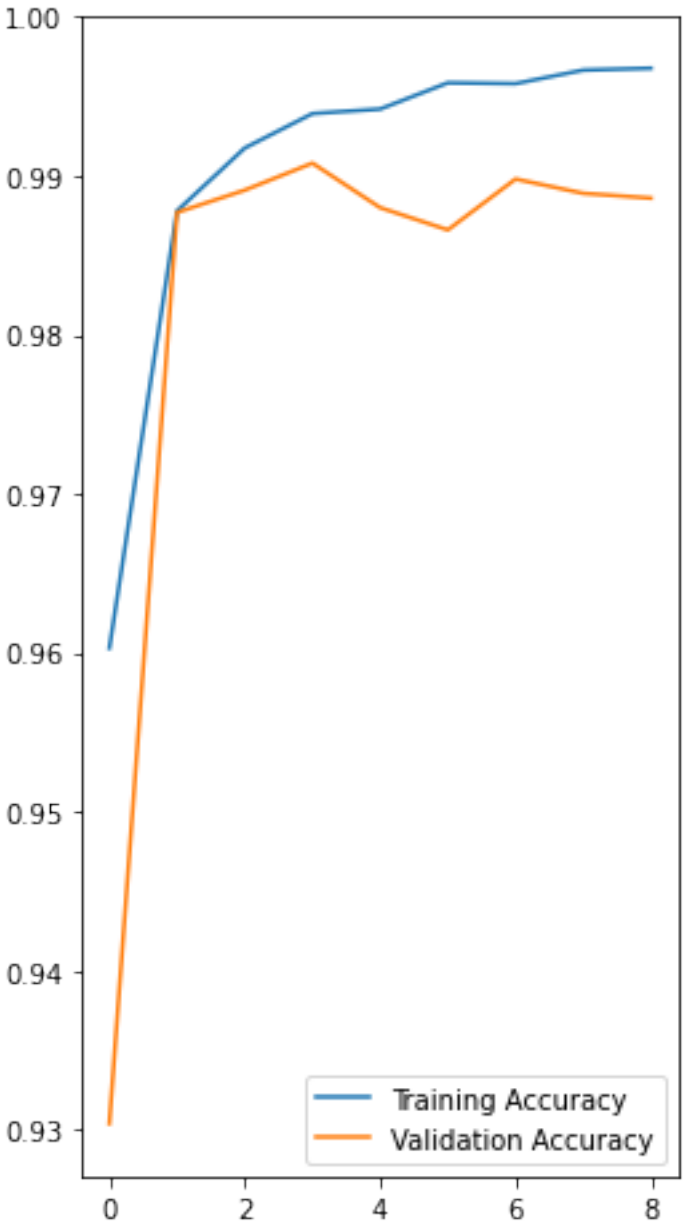
[10]:
```
history = model.fit(
    dstrain,
    epochs=30,
    validation_data=dstest,
    callbacks=[
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',
            patience=5,
        ),
        tf.keras.callbacks.ModelCheckpoint(
            'model.h5',
            monitor='val_loss',
            save_best_only=True,
            verbose=1)
    ]
)
```

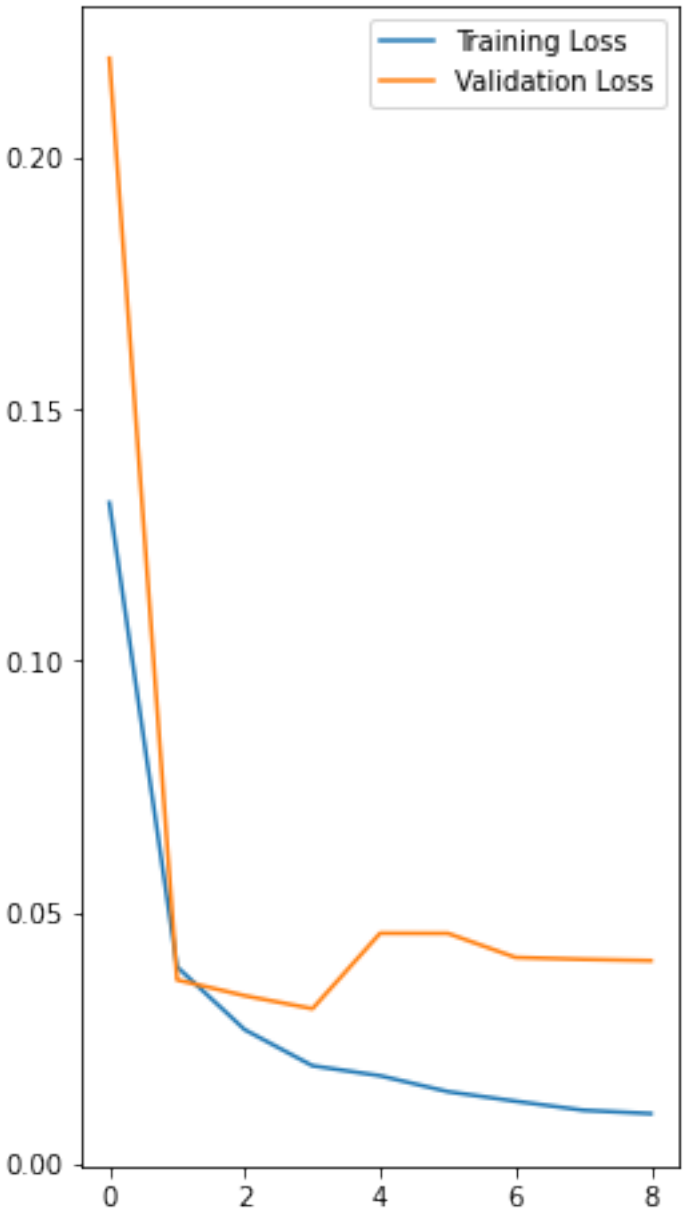
```
Epoch 1/30
2022-04-24 22:38:03.283133: I tensorflow/stream_executor/cuda/cuda_dnn.cc:368]
Loaded cuDNN version 8303
461/469 [============================>.] - ETA: 0s - loss: 0.1330 - accuracy:
0.9598
Epoch 1: val_loss improved from inf to 0.21989, saving model to model.h5
469/469 [==============================] - 8s 5ms/step - loss: 0.1315 -
accuracy: 0.9603 - val_loss: 0.2199 - val_accuracy: 0.9304
Epoch 2/30
465/469 [============================>.] - ETA: 0s - loss: 0.0392 - accuracy:
0.9878
Epoch 2: val_loss improved from 0.21989 to 0.03657, saving model to model.h5
469/469 [==============================] - 2s 5ms/step - loss: 0.0391 -
accuracy: 0.9878 - val_loss: 0.0366 - val_accuracy: 0.9877
Epoch 3/30
469/469 [==============================] - ETA: 0s - loss: 0.0267 - accuracy:
0.9918
Epoch 3: val_loss improved from 0.03657 to 0.03342, saving model to model.h5
469/469 [==============================] - 2s 5ms/step - loss: 0.0267 -
accuracy: 0.9918 - val_loss: 0.0334 - val_accuracy: 0.9891
Epoch 4/30
466/469 [============================>.] - ETA: 0s - loss: 0.0196 - accuracy:
0.9939
Epoch 4: val_loss improved from 0.03342 to 0.03083, saving model to model.h5
469/469 [==============================] - 2s 5ms/step - loss: 0.0195 -
accuracy: 0.9939 - val_loss: 0.0308 - val_accuracy: 0.9908
Epoch 5/30
467/469 [============================>.] - ETA: 0s - loss: 0.0175 - accuracy:
0.9942
Epoch 5: val_loss did not improve from 0.03083
469/469 [==============================] - 2s 5ms/step - loss: 0.0175 -
accuracy: 0.9942 - val_loss: 0.0458 - val_accuracy: 0.9880
```

```
Epoch 6/30
466/469 [============================>.] - ETA: 0s - loss: 0.0143 - accuracy:
0.9959
Epoch 6: val_loss did not improve from 0.03083
469/469 [==============================] - 2s 5ms/step - loss: 0.0143 -
accuracy: 0.9959 - val_loss: 0.0458 - val_accuracy: 0.9866
Epoch 7/30
466/469 [============================>.] - ETA: 0s - loss: 0.0124 - accuracy:
0.9958
Epoch 7: val_loss did not improve from 0.03083
469/469 [==============================] - 2s 5ms/step - loss: 0.0124 -
accuracy: 0.9958 - val_loss: 0.0410 - val_accuracy: 0.9898
Epoch 8/30
465/469 [============================>.] - ETA: 0s - loss: 0.0105 - accuracy:
0.9967
Epoch 8: val_loss did not improve from 0.03083
469/469 [==============================] - 2s 5ms/step - loss: 0.0106 -
accuracy: 0.9966 - val_loss: 0.0406 - val_accuracy: 0.9889
Epoch 9/30
467/469 [============================>.] - ETA: 0s - loss: 0.0100 - accuracy:
0.9968
Epoch 9: val_loss did not improve from 0.03083
469/469 [==============================] - 2s 5ms/step - loss: 0.0100 -
accuracy: 0.9968 - val_loss: 0.0404 - val_accuracy: 0.9886
```

Plot the accuracies and the losses across the range of epochs

[11]:
```
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.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.savefig('../paper/figs/loss.svg', format='svg')
plt.show()
```


1.00
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0
2
4
6
8
Training Accuracy
Validation Accuracy


Training Loss
Validation Loss
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8