CPE4903 Project: MNIST Handwritten Digit Classification

In this mini-project, you will develop a CNN model for the handwritten digit classifier.

- Use the companion notebook file, `CPE_4903_MNIST_NN`, as a reference and follow the steps to train and test the model.
- Performance requirement: the accuracy on the test data needs to be better than 99%
- You will save the parameters of the model at the end, which will be deployed on Raspberry Pi.

mnist_2layers_arch.png

Load tool modules

```
import numpy as np
import matplotlib.pyplot as plt


import tensorflow as tf
from tensorflow import keras
# from keras.utils import np_utils
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from keras.models import load_model
```

Load CNN models

```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dropout
```

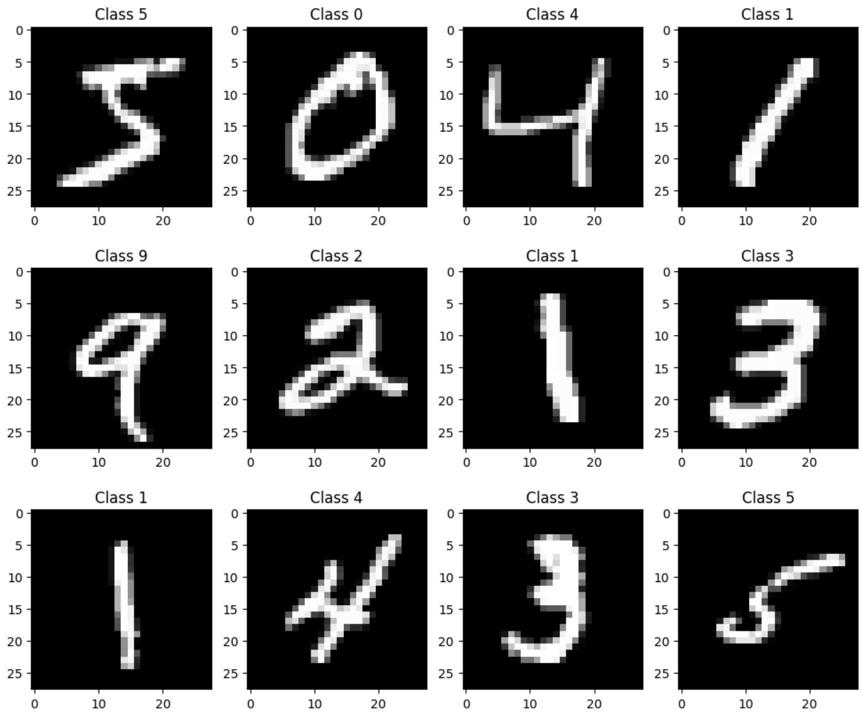
Load the dataset

```
from keras.datasets import mnist


(X_train, y_train), (X_test, y_test) = mnist.load_data()

print("X_train original shape", X_train.shape)
print("y_train original shape", y_train.shape)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
X_train original shape (60000, 28, 28)
y_train original shape (60000,)
```

Show 10 input images

```
plt.figure(figsize=(12,10))

for i in range(12):
    plt.subplot(3,4,i+1)
    plt.imshow(X_train[i], cmap='gray', interpolation='none')
    plt.title(f"Class {y_train[i]}")
```



Build the CNN Model

Pre-process the data:

1. Reshape X and Y to $(m, 28, 28, 1)$, where $m =$ # of samples in the dataset

2. Normalize the pixels for each image.

3. Convert the output labels (y_train and y_test) to categorical data.

```
m = X_train.shape[0]
test = X_test.shape[0]
print(f'The number of samples is {m}')

X_train = X_train.reshape(m, 28, 28, 1)
X_test = X_test.reshape(test, 28, 28, 1)
y_train = y_train.reshape(-1,1)
y_test = y_test.reshape(-1,1)

print(f'Train: {X_train.shape}')
print(f'Test: {X_test.shape}')
```

```
The number of samples is 60000
Train: (60000, 28, 28, 1)
Test: (10000, 28, 28, 1)
```

Normalize the pixels

```
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255
X_test /= 255
```

Convert the output labels (y_train and y_test) to categorical data

```
num_classes = 10

Y_train = keras.utils.to_categorical(y_train, num_classes)
Y_test = keras.utils.to_categorical(y_test, num_classes)
```

```
y_train[0:5]
```

```
array([[5],
       [0],
       [4],
```

```
           [1],
           [9]], dtype=uint8)
```

```
Y_train[0:5]
```

```
array([[0., 0., 0., 0., 0., 1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 1.]], dtype=float32)
```

```
Y_train.shape
```

```
(60000, 10)
```

```
y_train.shape
```

```
(60000, 1)
```

Define the CNN model

Use CONV, POOL and FC layers to construct your CNN model. You will train and test the model after this step.

```
# initialize the model
model = Sequential()

# THE CONVOLUTIONAL LAYERS

# first layer
model.add(
    Conv2D(filters=16, kernel_size=(2, 2), input_shape=(28, 28, 1), activation='relu', padding='same')
)
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
# output image size: (14, 14, 16)

# second layer
model.add(
    Conv2D(filters=32, kernel_size=(2, 2), activation='relu', padding='same')
)
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
# output image size: (7, 7, 32)

# third layer
model.add(
    Conv2D(filters=64, kernel_size=(2, 2), activation='relu', padding="same")
)
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
# output image size: (3, 3, 64)

# fourth layer
model.add(
    Conv2D(filters=128, kernel_size=(2, 2), activation='relu', padding='same')
)
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
# output image size: (1, 1, 128)

# FLATTEN
model.add(Flatten())

# THE FULLY CONNECTED LAYERS

# first fully connected layer
model.add(Dense(units=784, activation='relu'))

# second fully connected layer
model.add(Dense(units=392, activation='relu'))

# third fully connected layer
model.add(Dense(units=128, activation='relu'))

# final layer
model.add(Dense(units=num_classes, activation='softmax'))
```

Print the model summary that shows the output shape and # of parameters for each layer.

```
model.summary()
```

```
Model: "sequential_16"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_49 (Conv2D)          (None, 28, 28, 16)        80        
                                                                 
 max_pooling2d_49 (MaxPooli  (None, 14, 14, 16)        0         
 ng2D)                                                           
                                                                 
 conv2d_50 (Conv2D)          (None, 14, 14, 32)        2080      
                                                                 
 max_pooling2d_50 (MaxPooli  (None, 7, 7, 32)          0         
 ng2D)                                                           
                                                                 
 conv2d_51 (Conv2D)          (None, 7, 7, 64)          8256      
                                                                 
 max_pooling2d_51 (MaxPooli  (None, 3, 3, 64)          0         
 ng2D)                                                           
                                                                 
 conv2d_52 (Conv2D)          (None, 3, 3, 128)         32896     
                                                                 
 max_pooling2d_52 (MaxPooli  (None, 1, 1, 128)         0         
 ng2D)                                                           
                                                                 
 flatten_15 (Flatten)        (None, 128)               0         
                                                                 
 dense_62 (Dense)            (None, 784)               101136    
                                                                 
 dense_63 (Dense)            (None, 392)               307720    
                                                                 
 dense_64 (Dense)            (None, 128)               50304     
                                                                 
 dense_65 (Dense)            (None, 10)                1290      
                                                                 
=================================================================
Total params: 503762 (1.92 MB)
Trainable params: 503762 (1.92 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Train the CNN Model

```
# compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
# training
history = model.fit(X_train, Y_train, epochs=30, verbose=1, batch_size=512, validation_split=0.20)
```

```
Epoch 1/30
94/94 [==============================] - 2s 17ms/step - loss: 0.0313 - accuracy: 0.9916 - val_loss: 0.0563 - val_accuracy: 0.983
Epoch 2/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0125 - accuracy: 0.9964 - val_loss: 0.0450 - val_accuracy: 0.989
Epoch 3/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0069 - accuracy: 0.9979 - val_loss: 0.0594 - val_accuracy: 0.986
Epoch 4/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0039 - accuracy: 0.9988 - val_loss: 0.0542 - val_accuracy: 0.990
Epoch 5/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0055 - accuracy: 0.9984 - val_loss: 0.0499 - val_accuracy: 0.989
Epoch 6/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0021 - accuracy: 0.9994 - val_loss: 0.0481 - val_accuracy: 0.990
Epoch 7/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0037 - accuracy: 0.9992 - val_loss: 0.0507 - val_accuracy: 0.988
Epoch 8/30
94/94 [==============================] - 1s 11ms/step - loss: 9.6121e-04 - accuracy: 0.9997 - val_loss: 0.0466 - val_accuracy: 0
Epoch 9/30
94/94 [==============================] - 1s 12ms/step - loss: 0.0020 - accuracy: 0.9995 - val_loss: 0.0643 - val_accuracy: 0.988
Epoch 10/30
94/94 [==============================] - 1s 12ms/step - loss: 0.0019 - accuracy: 0.9994 - val_loss: 0.0521 - val_accuracy: 0.990
Epoch 11/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0022 - accuracy: 0.9993 - val_loss: 0.0859 - val_accuracy: 0.985
Epoch 12/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0064 - accuracy: 0.9980 - val_loss: 0.0457 - val_accuracy: 0.991
Epoch 13/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0030 - accuracy: 0.9990 - val_loss: 0.0596 - val_accuracy: 0.989
Epoch 14/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0055 - accuracy: 0.9983 - val_loss: 0.0605 - val_accuracy: 0.988
Epoch 15/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0017 - accuracy: 0.9993 - val_loss: 0.0521 - val_accuracy: 0.990
Epoch 16/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0050 - accuracy: 0.9985 - val_loss: 0.0525 - val_accuracy: 0.989
Epoch 17/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0015 - accuracy: 0.9995 - val_loss: 0.0475 - val_accuracy: 0.990
Epoch 18/30
94/94 [==============================] - 1s 11ms/step - loss: 9.3043e-04 - accuracy: 0.9998 - val_loss: 0.0584 - val_accuracy: 0
Epoch 19/30
```

```
94/94 [==============================] - 1s 11ms/step - loss: 8.3470e-04 - accuracy: 0.9997 - val_loss: 0.0584 - val_accuracy: 0
Epoch 20/30
94/94 [==============================] - 1s 12ms/step - loss: 0.0061 - accuracy: 0.9979 - val_loss: 0.0582 - val_accuracy: 0.987
Epoch 21/30
94/94 [==============================] - 1s 13ms/step - loss: 0.0041 - accuracy: 0.9986 - val_loss: 0.0584 - val_accuracy: 0.989
Epoch 22/30
94/94 [==============================] - 1s 12ms/step - loss: 0.0015 - accuracy: 0.9995 - val_loss: 0.0636 - val_accuracy: 0.988
Epoch 23/30
94/94 [==============================] - 1s 11ms/step - loss: 0.0020 - accuracy: 0.9994 - val_loss: 0.0449 - val_accuracy: 0.992
Epoch 24/30
94/94 [==============================] - 1s 11ms/step - loss: 4.9715e-04 - accuracy: 0.9999 - val_loss: 0.0603 - val_accuracy: 0
Epoch 25/30
94/94 [==============================] - 1s 11ms/step - loss: 2.5366e-04 - accuracy: 0.9999 - val_loss: 0.0530 - val_accuracy: 0
Epoch 26/30
94/94 [==============================] - 1s 11ms/step - loss: 9.8178e-05 - accuracy: 0.9999 - val_loss: 0.0528 - val_accuracy: 0
Epoch 27/30
94/94 [==============================] - 1s 11ms/step - loss: 3.8082e-05 - accuracy: 1.0000 - val_loss: 0.0523 - val_accuracy: 0
Epoch 28/30
94/94 [==============================] - 1s 11ms/step - loss: 1.2787e-05 - accuracy: 1.0000 - val_loss: 0.0537 - val_accuracy: 0
```

Compare Loss and Accuracy Performance for train and validation data

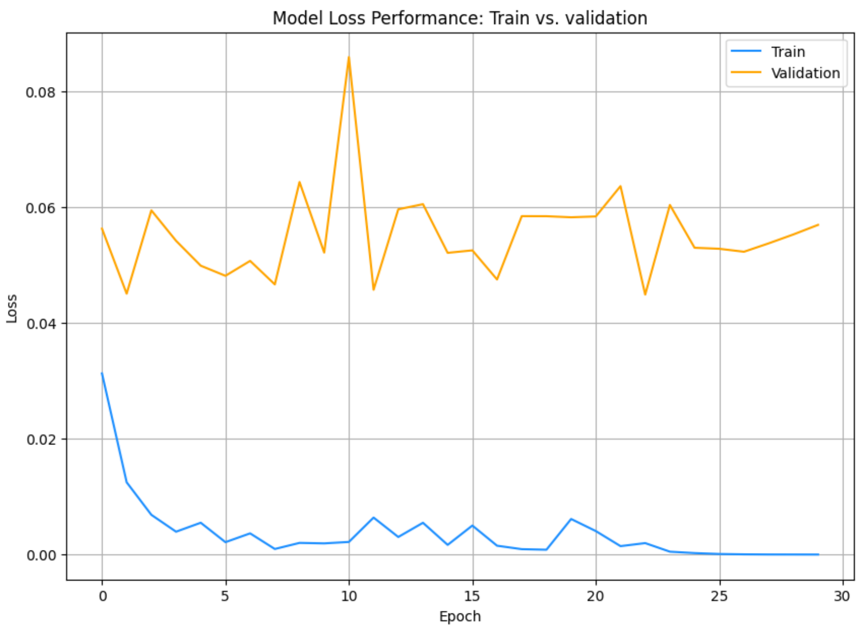
Plot the loss data, for both train and validation data

```
history.history.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

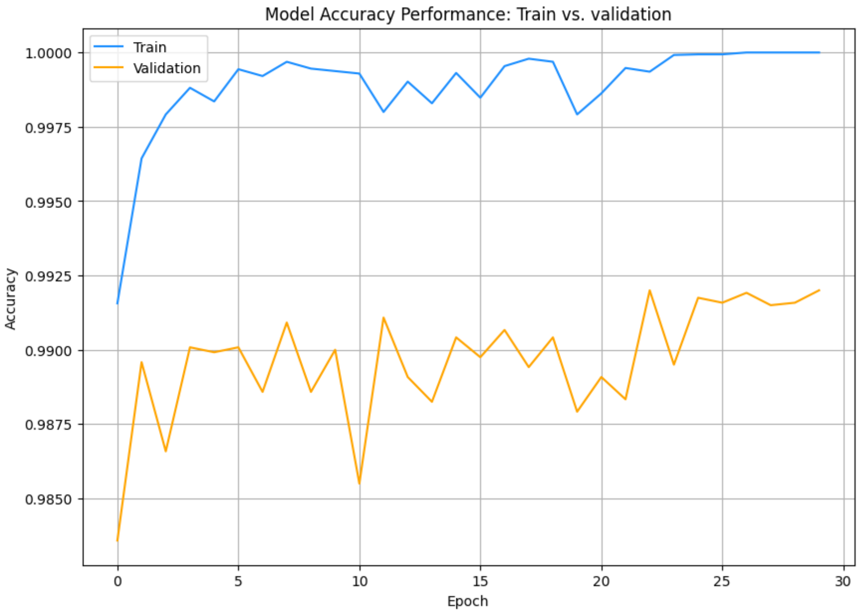
```
J = history.history['loss']  # training loss
J_val = history.history['val_loss'] # validation loss
```

```
plt.figure(figsize=(10,7))

plt.title('Model Loss Performance: Train vs. validation')
plt.plot(J, color='DodgerBlue', label='Train')
plt.plot(J_val, color='orange', label='Validation')

plt.ylabel('Loss')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()
```



Plot the accuracy data, for both train and validation data

```
accu = history.history['accuracy']  # training accuracy
accu_val = history.history['val_accuracy'] # validation accuracy


plt.figure(figsize=(10,7))

plt.title('Model Accuracy Performance: Train vs. validation')
plt.plot(accu, color='DodgerBlue', label='Train')
plt.plot(accu_val, color='orange', label='Validation')

plt.ylabel('Accuracy')
plt.xlabel('Epoch')

plt.legend()
plt.grid()
plt.show()
```



Test the CNN Model

```
score = model.evaluate(X_test, Y_test, verbose=1)
```

```
313/313 [==============================] - 1s 3ms/step - loss: 0.0596 - accuracy: 0.9909
```

Print the final loss and accuracy of the test data

```
J_test = score[0]
test_accuracy = score[1]

print(f'The final loss on test data is {J_test:.4f}')
print(f'The accuracy on test data is {(test_accuracy * 100):.2f}%')
```

```
The final loss on test data is 0.0596
The accuracy on test data is 99.09%
```

Save the CNN model parameters

```
model.save('MNIST_CNN.h5')
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: You are saving your model as an HDF5 file v:
  saving_api.save_model(
```

Conclusion

You will add remarks on:

1. Number of parameters for the three models: MLP, baseline CNN, and your CNN

2. Performance (accuracy) comparison

3. Anything else you tried and observed while traing the model

Question 1

Number of parameters in MLP: 669,706
Number of parameters in baseline CNN: 542,230
Number of paramters in my CNN: 503762
As the number of convolutional layers increase, the number of trainable parameters seem to be going down.

Question 2

Testing accuracy for MLP: 97.35%
Testing accuracy for baseline CNN: 95.44%
Testing accuracy for my CNN: 99.09%
From the testing accuracy, it seems like that the number of fully connected layers along with the convolutional layers play an essential part in the accuracy. The MLP had 3 FC layers, whereas the baseline CNN had only 2 FC layers and 1 Conv layer. My model has 4 FC layers and 4 Conv layers, which means that it's more deep than the other too models, hence, giving a better performance. Furthermore, I've used more filters in the convolutional layers, which means that relatively more higher level features are being extracted in this model.

Question 3

I tried to adjust the validation ratio to and the batch size to increase the accuracy. Validation didn't really result in a huge change, but increasing the batch size gave a rapid boost to the time taken per epoch as well because increasing batch size means decreasing the number of batches, or the number of steps taken in each epoch.

Remember to turn in both the notebook and the pdf version.