Getting started with Colab in my Simplilearn DL class

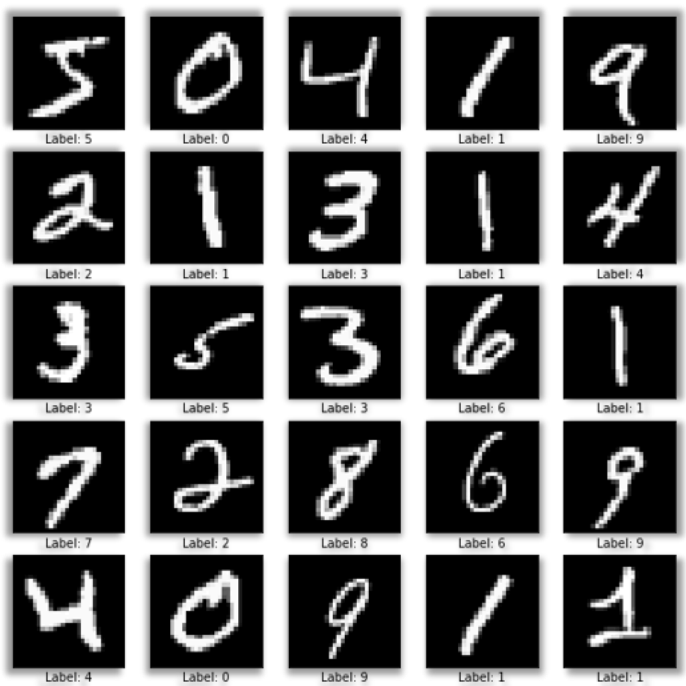
Import Tensorflow and check it's version

```
import tensorflow as tf
print("Tensorflow version:", tf.__version__)
```

```
Tensorflow version: 2.18.0
```

Load the MNIST dataset

The MNIST dataset is a large collection of handwritten digits commonly used for training and testing in the field of machine learning. It is one of the most well-known datasets for evaluating the performance of image processing and pattern recognition algorithms.




```
mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
print("Exploring the number of training data samples")
print(x_train.shape)
```

```
Exploring the number of training data samples
(60000, 28, 28)
```

```
print(type(x_train))
```

```
<class 'numpy.ndarray'>
```

```
print(y_train.shape)
```

```
(60000,)
```

```
print(y_train)
```

```
[5 0 4 ... 5 6 8]
```

```
print(y_train)
```

```
0
```

```
print(max(y_train))
```

```
9
```

```
print(set(y_train.tolist()))
```

```
{0, 1, 2, 3, 4, 5, 6, 7, 8, 9}
```

```
print(set(y_train))
```

```
{np.uint8(0), np.uint8(1), np.uint8(2), np.uint8(3), np.uint8(4), np.uint8(5), np.uint8(6), np.uint8(7), np.uint8
```

```
print("Exploring the number of testing data samples")
```

```
Exploring the number of testing data samples
```

```
print(x_test.shape)
```

```
(10000, 28, 28)
```

```
print(y_test.shape)
```

```
(10000,)
```

```
print(x_test[0])
```

```
[[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0  84 185 159 151  60  36   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0 222 254 254 254 254 241 198 198 198 198 198 198
  198 198 170  52   0   0   0   0   0   0]
 [  0   0   0   0   0   0  67 114  72 114 163 227 254 225 254 254 254 250
  229 254 254 140   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0  17  66  14  67  67  67  59
   21 236 254 106   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   83 253 209  18   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  22
  233 255  83   0   0   0   0   0   0   0]
```

```
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 129
 254 238  44   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0  59 249
 254  62   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 133 254
 187   5   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   9 205 248
  58   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 126 254 182
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0  75 251 240  57
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0  19 221 254 166   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   3 203 254 219  35   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0  38 254 254  77   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0  31 224 254 115   1   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0 133 254 254  52   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0  61 242 254 254  52   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0 121 254 254 219  40   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0 121 254 207  18   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]]
```

In order to normalise our train and test datasets, we divide the pixel values present in every image by 255.

```
x_train = x_train/255.0
x_test = x_test/255.0
```

```
print("After data normalisation")
print(x_test[0])
```

```
  0.         0.         0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.52156863
  0.99607843 0.99607843 0.20392157 0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.23921569 0.94901961
  0.99607843 0.99607843 0.20392157 0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.4745098  0.99607843
  0.99607843 0.85882353 0.15686275 0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.4745098  0.99607843
  0.81176471 0.07058824 0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.        ]
 [0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.         0.         0.
  0.         0.         0.         0.        ]]
```

One hot encoding the labels

```
y_train_one_hot = tf.keras.utils.to_categorical(y_train,10)
y_test_one_hot = tf.keras.utils.to_categorical(y_test,10)
```

```
print("Before OHE")
print(y_train[0])
```

```
Before OHE
5
```

```
print("After OHE")
print(y_train_one_hot[0])
```

```
After OHE
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
```

```
print(x_train.shape)
```

```
(60000, 28, 28)
```

```
print(x_test.shape)
```

```
(10000, 28, 28)
```

```
# X_train is 60000 rows of 28x28 values(2d); we reshape it to 60000 x 784(1d)
# X_test is 10000 rows od data 28x28 values(2d); we reshape it to 10000 x 784(1d)
# 28x28 = 784 neurons
x_train_reshaped = x_train.reshape(60000,784)
x_test_reshaped = x_test.reshape(10000,784)
```

Note: We have hence loaded the data and completed all the necessary preprocessing steps.

Let us begin creating our first Neural Network Model

```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
```

```
model_mnist_digits = Sequential()
```

```
model_mnist_digits.add(Dense(10, input_shape=(784,), activation='softmax'))
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_sha
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
model_mnist_digits.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 10)	7,850

Total params: 7,850 (30.66 KB)
Trainable params: 7,850 (30.66 KB)
Non-trainable params: 0 (0.00 B)

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

```
# Training the model

training = model_mnist_digits.fit(x_train_reshaped,y_train_one_hot,epochs=5, validation_split=0.2)
```

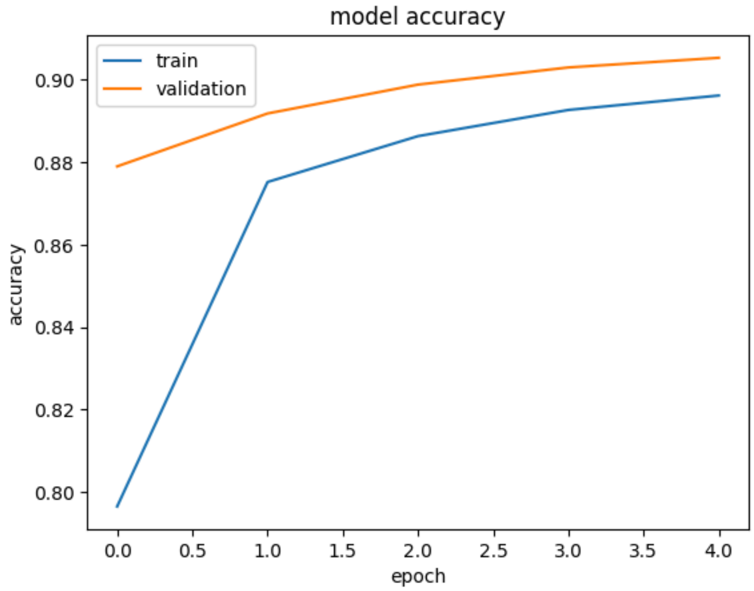
```
Epoch 1/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 5s 3ms/step - accuracy: 0.6821 - loss: 1.2311 - val_accuracy: 0.8790 - val_loss: 0
Epoch 2/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.8708 - loss: 0.5170 - val_accuracy: 0.8918 - val_loss: 0
Epoch 3/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.8852 - loss: 0.4384 - val_accuracy: 0.8988 - val_loss: 0
Epoch 4/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - accuracy: 0.8910 - loss: 0.4052 - val_accuracy: 0.9030 - val_loss: 0
Epoch 5/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.8952 - loss: 0.3797 - val_accuracy: 0.9053 - val_loss: 0
```

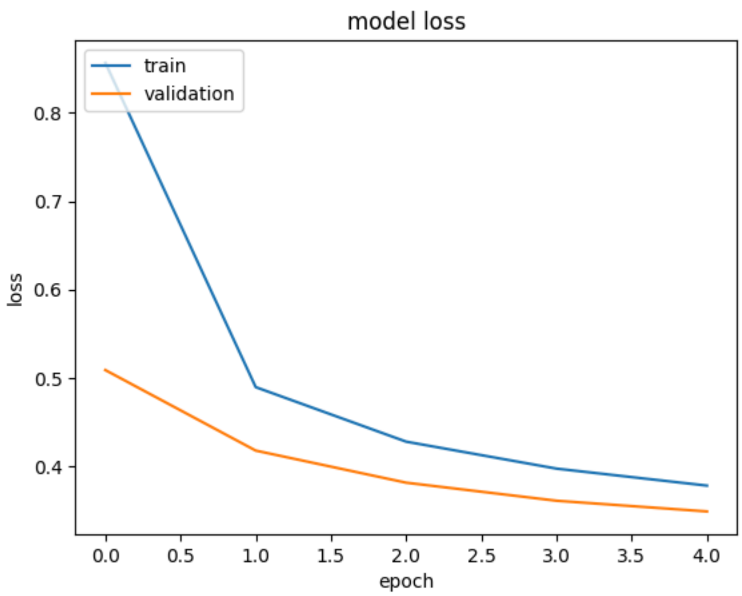
```
#evaluate the model
test_loss, test_acc = model_mnist_digits.evaluate(x_test_reshaped, y_test_one_hot)
print('Test accuracy:', test_acc)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8923 - loss: 0.3991
Test accuracy: 0.9067999720573425
```

```
import matplotlib.pyplot as plt
%matplotlib inline
# list all data in training
print(training.history.keys())
# summarize training for accuracy
plt.plot(training.history['accuracy']) # training accuracy values
plt.plot(training.history['val_accuracy']) #validation accuracy values
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
# summarize traning for loss
plt.plot(training.history['loss']) # training loss values
plt.plot(training.history['val_loss']) #validation loss values
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

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






```
#evaluate the model
test_loss, test_acc = model_mnist_digits.evaluate(x_test_reshaped, y_test_one_hot)
print('Test accuracy:', test_acc)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8923 - loss: 0.3991
Test accuracy: 0.9067999720573425
```

Build another model with 1 hidden layer. This model would have 3 layers in total - input, hidden & output layers

```
model_mnist_digits_hidden = Sequential()
```

```
model_mnist_digits_hidden.add(Dense(20, activation = "relu", input_shape=(784,))) #input layer with hidden layer
model_mnist_digits_hidden.add(Dense(10, activation = "softmax")) #output layer
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_sha
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
model_mnist_digits_hidden.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 20)	15,700
dense_2 (Dense)	(None, 10)	210

Total params: 15,910 (62.15 KB)
Trainable params: 15,910 (62.15 KB)
Non-trainable params: 0 (0.00 B)

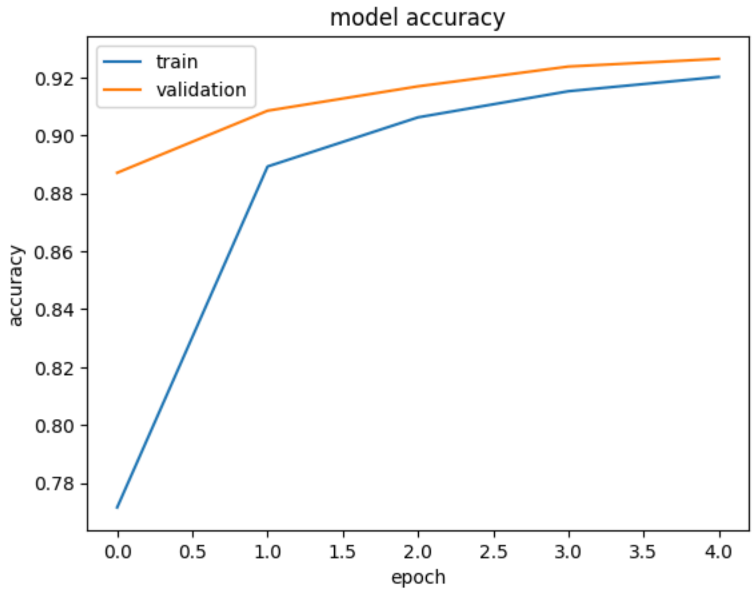
```
model_mnist_digits_hidden.compile(optimizer='SGD', loss='categorical_crossentropy', metrics=['accuracy'])
```

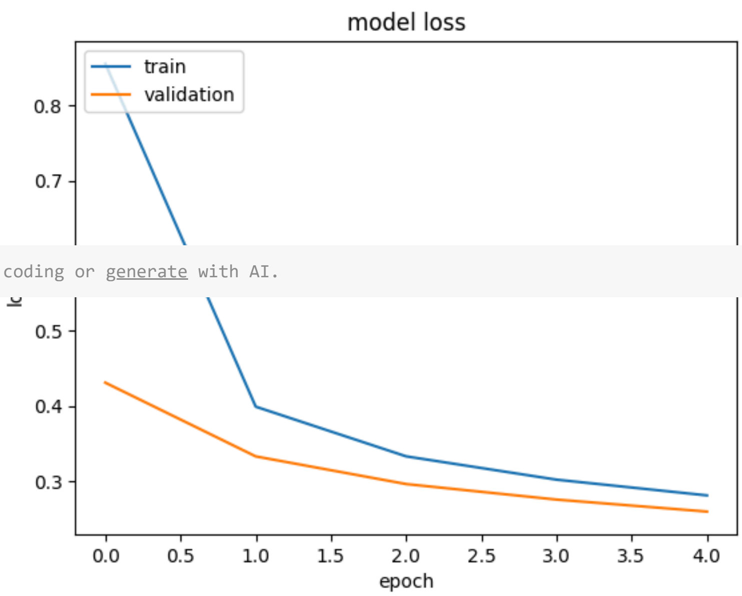
```
training2 = model_mnist_digits_hidden.fit(x_train_reshaped,y_train_one_hot,epochs=5, validation_split=0.2)
```

```
Epoch 1/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 4s 3ms/step - accuracy: 0.6389 - loss: 1.2919 - val_accuracy: 0.8871 - val_loss: 0
Epoch 2/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - accuracy: 0.8816 - loss: 0.4263 - val_accuracy: 0.9085 - val_loss: 0
Epoch 3/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 0.9015 - loss: 0.3490 - val_accuracy: 0.9169 - val_loss: 0
Epoch 4/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.9159 - loss: 0.3023 - val_accuracy: 0.9237 - val_loss: 0
Epoch 5/5
1500/1500 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - accuracy: 0.9191 - loss: 0.2885 - val_accuracy: 0.9264 - val_loss: 0
```

```
# list all data in training
print(training2.history.keys())
# summarize training for accuracy
plt.plot(training2.history['accuracy']) # training accuracy values
plt.plot(training2.history['val_accuracy']) #validation accuracy values
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
# summarize traning for loss
plt.plot(training2.history['loss']) # training loss values
plt.plot(training2.history['val_loss']) #validation loss values
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

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





Start coding or generate with AI.