

```
In [6]: import tensorflow as tf
        from tensorflow import keras
        import matplotlib.pyplot as plt
        import numpy as np
```

1. Load the Dataset

```
In [8]: #Load dataset
        (x_train,y_train), (x_test,y_test) = keras.datasets.mnist.load_data()
```

2. Analyze and explore the dataset

```
In [10]: #Analyze the data
         x_train.shape
```

```
Out[10]: (60000, 28, 28)
```

```
In [11]: y_train.shape
```

```
Out[11]: (60000,)
```

```
In [12]: x_test.shape
```

```
Out[12]: (10000, 28, 28)
```

```
In [83]: x_train[10]
```

```

Out[83]: array([[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.      , 0.16470588, 0.4627451 , 0.85882353, 0.65098039,
0.4627451 , 0.4627451 , 0.02352941, 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.40392157, 0.94901961, 0.99607843, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.25882353, 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.07058824, 0.90980392, 0.99607843, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.93333333, 0.2745098 , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.40784314, 0.95686275, 0.99607843, 0.87843137,
0.99607843, 0.99607843, 0.99607843, 0.55294118, 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.81176471, 0.99607843, 0.82352941,
0.99607843, 0.99607843, 0.99607843, 0.13333333, 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,

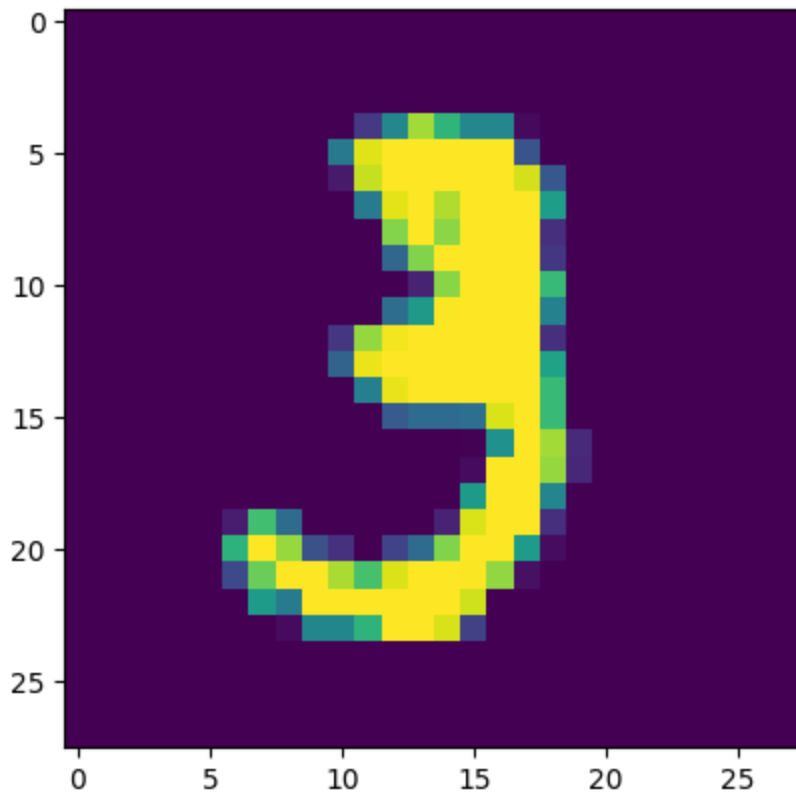
```

0. , 0. , 0.32941176, 0.80784314, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.16078431, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.09411765, 0.81960784,
0.99607843, 0.99607843, 0.99607843, 0.67058824, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.35686275, 0.5372549 , 0.99215686,
0.99607843, 0.99607843, 0.99607843, 0.43921569, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.15686275, 0.83921569, 0.98039216, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.13333333, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.31764706, 0.96862745, 0.99607843, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.57254902, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.43137255, 0.96470588, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.67058824, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.28627451, 0.34901961, 0.34901961,
0.36470588, 0.94117647, 0.99607843, 0.67058824, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.00392157, 0.50196078, 0.99607843, 0.85882353, 0.12156863,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.02745098, 0.99607843, 0.99607843, 0.83921569, 0.10980392,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.54117647, 0.99607843, 0.99607843, 0.45490196, 0. ,

	[0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.],		
	[0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.0745098	, 0.69411765,	0.35294118,	0.	,
	0.	, 0.	, 0.	, 0.	, 0.09803922,	
	0.94117647,	0.99607843,	0.99607843,	0.13333333,	0.	,
	0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.],		
	[0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.64313725,	0.99607843,	0.84313725,	0.24705882,	
	0.14117647,	0.	, 0.2	, 0.34901961,	0.80784314,	
	0.99607843,	0.99607843,	0.54509804,	0.03137255,	0.	,
	0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.],		
	[0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.22352941,	0.77254902,	0.99607843,	0.99607843,	
	0.87058824,	0.70588235,	0.94509804,	0.99607843,	0.99607843,	
	0.99215686,	0.83529412,	0.04313725,	0.	, 0.	,
	0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.],		
	[0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.54901961,	0.41176471,	0.99607843,	
	0.99607843,	0.99607843,	0.99607843,	0.99607843,	0.99607843,	
	0.9254902	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.],		
	[0.	, 0.	, 0.	, 0.	, 0.	,
	0.	, 0.	, 0.	, 0.02745098,	0.45882353,	
	0.45882353,	0.64705882,	0.99607843,	0.99607843,	0.9372549	,
	0.19607843,	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.]])		

2.1 plot sample data to get a better visual representation

```
In [15]: #plot sample data to get a better visual representation  
plt.imshow(x_train[10])  
plt.show()
```



2.2 Check the respective image label

```
In [17]: # Check the respective image label  
y_train[10]
```

Out[17]: 3

```
In [18]: x_train.shape
```

Out[18]: (60000, 28, 28)

```
In [19]: len(x_train)
```

Out[19]: 60000

3. Normalize the pixel data

```
In [31]: #Normalized pixel data  
x_train = x_train/255  
x_test = x_test/255
```

```
In [85]: x_train[10]
```

```

Out[85]: array([[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.      , 0.16470588, 0.4627451 , 0.85882353, 0.65098039,
0.4627451 , 0.4627451 , 0.02352941, 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.40392157, 0.94901961, 0.99607843, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.25882353, 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.07058824, 0.90980392, 0.99607843, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.93333333, 0.2745098 , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.40784314, 0.95686275, 0.99607843, 0.87843137,
0.99607843, 0.99607843, 0.99607843, 0.55294118, 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.81176471, 0.99607843, 0.82352941,
0.99607843, 0.99607843, 0.99607843, 0.13333333, 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , ],
[0.      , 0.      , 0.      , 0.      , 0.      ,
0.      , 0.      , 0.      , 0.      , 0.      ,

```

0. , 0. , 0.32941176, 0.80784314, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.16078431, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.09411765, 0.81960784,
0.99607843, 0.99607843, 0.99607843, 0.67058824, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.35686275, 0.5372549 , 0.99215686,
0.99607843, 0.99607843, 0.99607843, 0.43921569, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.15686275, 0.83921569, 0.98039216, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.13333333, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.31764706, 0.96862745, 0.99607843, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.57254902, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.43137255, 0.96470588, 0.99607843, 0.99607843,
0.99607843, 0.99607843, 0.99607843, 0.67058824, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.28627451, 0.34901961, 0.34901961,
0.36470588, 0.94117647, 0.99607843, 0.67058824, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.00392157, 0.50196078, 0.99607843, 0.85882353, 0.12156863,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.02745098, 0.99607843, 0.99607843, 0.83921569, 0.10980392,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.],
[0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.54117647, 0.99607843, 0.99607843, 0.45490196, 0. ,

[illegible]

4. Flattening the images

```
In [36]: x_train_flattened = x_train.reshape(len(x_train),28*28)
x_train_flattened.shape
```

```
Out[36]: (60000, 784)
```

```
In [38]: x_test_flattened = x_test.reshape(len(x_test),28*28)
x_test_flattened.shape
```

```
Out[38]: (10000, 784)
```

5.1 Building the first Model with a single Dense Layer

```
In [41]: model = keras.Sequential(
    [
        keras.layers.Dense(10, input_shape= (784,) ,activation='sigmoid')
    ]
)

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy', #we have categories of output
              metrics=['accuracy'])

model.fit(x_train_flattened,y_train,epochs=5)
```

C:\Anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:93: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/5
1875/1875 ————— 2s 771us/step - accuracy: 0.8183 - loss: 0.7104
Epoch 2/5
1875/1875 ————— 1s 756us/step - accuracy: 0.9149 - loss: 0.3097
Epoch 3/5
1875/1875 ————— 1s 748us/step - accuracy: 0.9207 - loss: 0.2862
Epoch 4/5
1875/1875 ————— 1s 780us/step - accuracy: 0.9246 - loss: 0.2667
Epoch 5/5
1875/1875 ————— 1s 773us/step - accuracy: 0.9260 - loss: 0.2671
```

```
Out[41]: <keras.src.callbacks.history.History at 0x17968cc54c0>
```

5.2 Evaluating the model

```
In [44]: #Evaluating the model
model.evaluate(x_test_flattened,y_test)
```

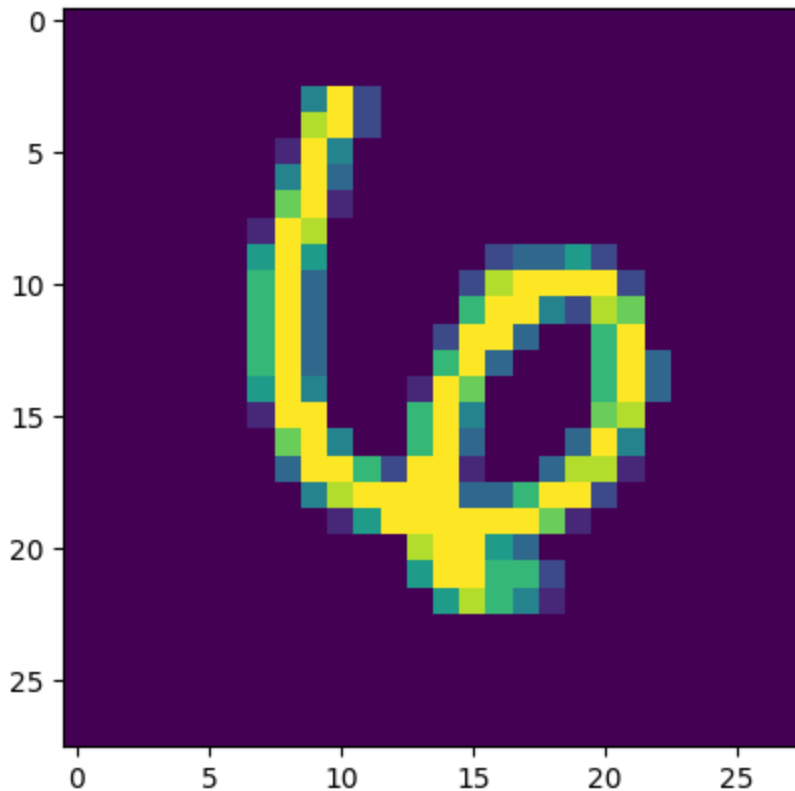
313/313 ————— 0s 827us/step - accuracy: 0.9161 - loss: 0.3025

Out[44]: [0.26626142859458923, 0.9265999794006348]

5.3 Testing the model with a sample prediction

In [47]: `plt.imshow(x_test[22])`

Out[47]: <matplotlib.image.AxesImage at 0x17968b663c0>



In [49]: `k = model.predict(x_test[22].reshape(1,784))`
`np.argmax(k)`

1/1 ————— 0s 47ms/step

Out[49]: 6

In [51]: `y_peddicted_Labels = [np.argmax(i) for i in model.predict(x_test_flattened)]`

313/313 ————— 0s 465us/step

5.4 Building a confusion metrix to evaluate he performance

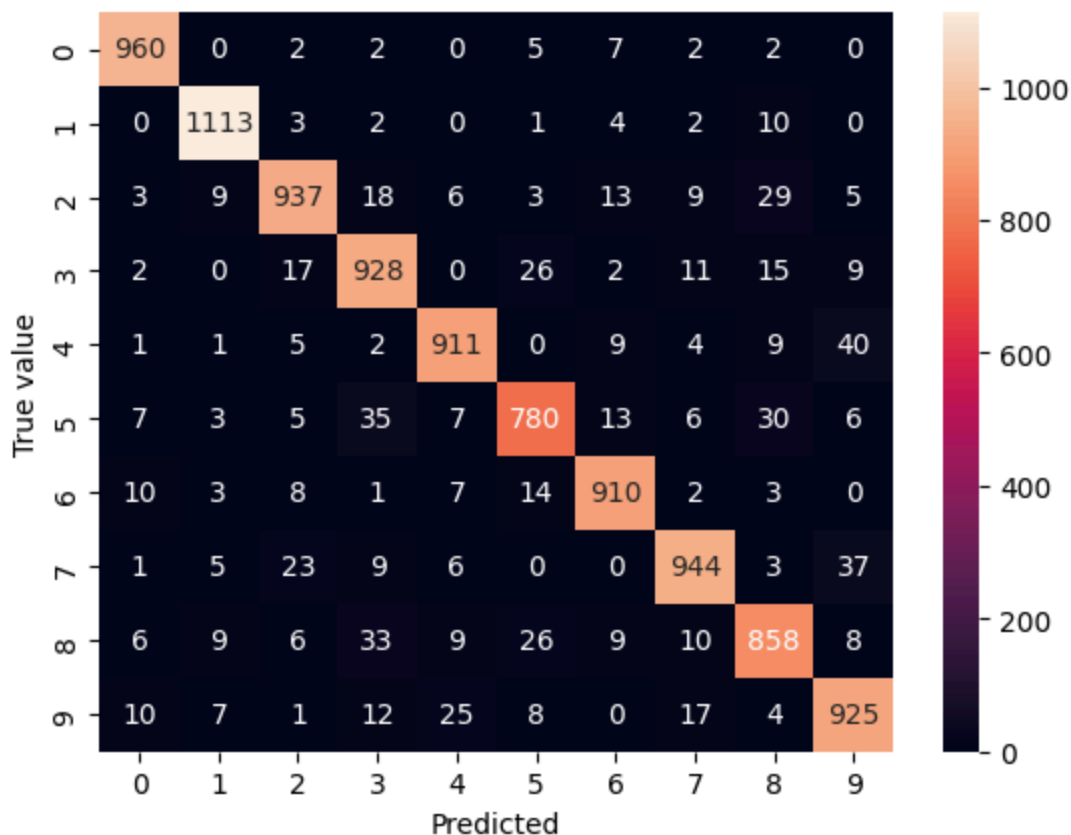
In [54]: `# Building a confusion metrix to evaluate he performance`
`cm = tf.math.confusion_matrix(labels=y_test,predictions=y_peddicted_Labels)`

cm

```
Out[54]: <tf.Tensor: shape=(10, 10), dtype=int32, numpy=
array([[ 960,    0,    2,    2,    0,    5,    7,    2,    2,    0],
       [    0, 1113,    3,    2,    0,    1,    4,    2,   10,    0],
       [    3,    9,  937,   18,    6,    3,   13,    9,   29,    5],
       [    2,    0,   17,  928,    0,   26,    2,   11,   15,    9],
       [    1,    1,    5,    2,  911,    0,    9,    4,    9,   40],
       [    7,    3,    5,   35,    7,  780,   13,    6,   30,    6],
       [   10,    3,    8,    1,    7,   14,  910,    2,    3,    0],
       [    1,    5,   23,    9,    6,    0,    0,  944,    3,   37],
       [    6,    9,    6,   33,    9,   26,    9,   10,  858,    8],
       [   10,    7,    1,   12,   25,    8,    0,   17,    4,  925]])>
```

```
In [56]: import seaborn as sns
```

```
In [58]: #Plotting the confusion matix using seaborn library for a better visual representat
sns.heatmap(cm, annot=True, fmt='d')
plt.xlabel("Predicted")
plt.ylabel("True value")
plt.show()
```



6.1 Building the second Model with a hidden layer (with 100 neurones)

```
In [61]: #building another model with hidden layer
model2 = keras.Sequential()
```

```
[
    #without keras flatten layer, because we are manually flattening the image
    #100 is hidden layer neurones and activation function is relu
    keras.layers.Dense(100, input_shape= (784,) ,activation='relu'),
    keras.layers.Dense(10 ,activation='sigmoid')
]
)

model2.compile(optimizer='adam',
               loss='sparse_categorical_crossentropy', #we have categories of output
               metrics=['accuracy'])

model2.fit(x_train_flattened,y_train,epochs=5)
```

Epoch 1/5

C:\Anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:93: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
 super().__init__(activity_regularizer=activity_regularizer, **kwargs)

1875/1875 ————— 2s 1ms/step - accuracy: 0.8780 - loss: 0.4451

Epoch 2/5

1875/1875 ————— 2s 1ms/step - accuracy: 0.9593 - loss: 0.1363

Epoch 3/5

1875/1875 ————— 2s 1ms/step - accuracy: 0.9736 - loss: 0.0908

Epoch 4/5

1875/1875 ————— 2s 1ms/step - accuracy: 0.9803 - loss: 0.0683

Epoch 5/5

1875/1875 ————— 2s 1ms/step - accuracy: 0.9829 - loss: 0.0547

Out[61]: <keras.src.callbacks.history.History at 0x17970bc7530>

6.2 Evaluating the model

In [64]: # evaluate model for training data
 model2.evaluate(x_train_flattened, y_train)

1875/1875 ————— 2s 776us/step - accuracy: 0.9860 - loss: 0.0443

Out[64]: [0.04461903125047684, 0.9861500263214111]

In [66]: # evaluate model for testing data
 model2.evaluate(x_test_flattened, y_test)

313/313 ————— 0s 823us/step - accuracy: 0.9682 - loss: 0.1031

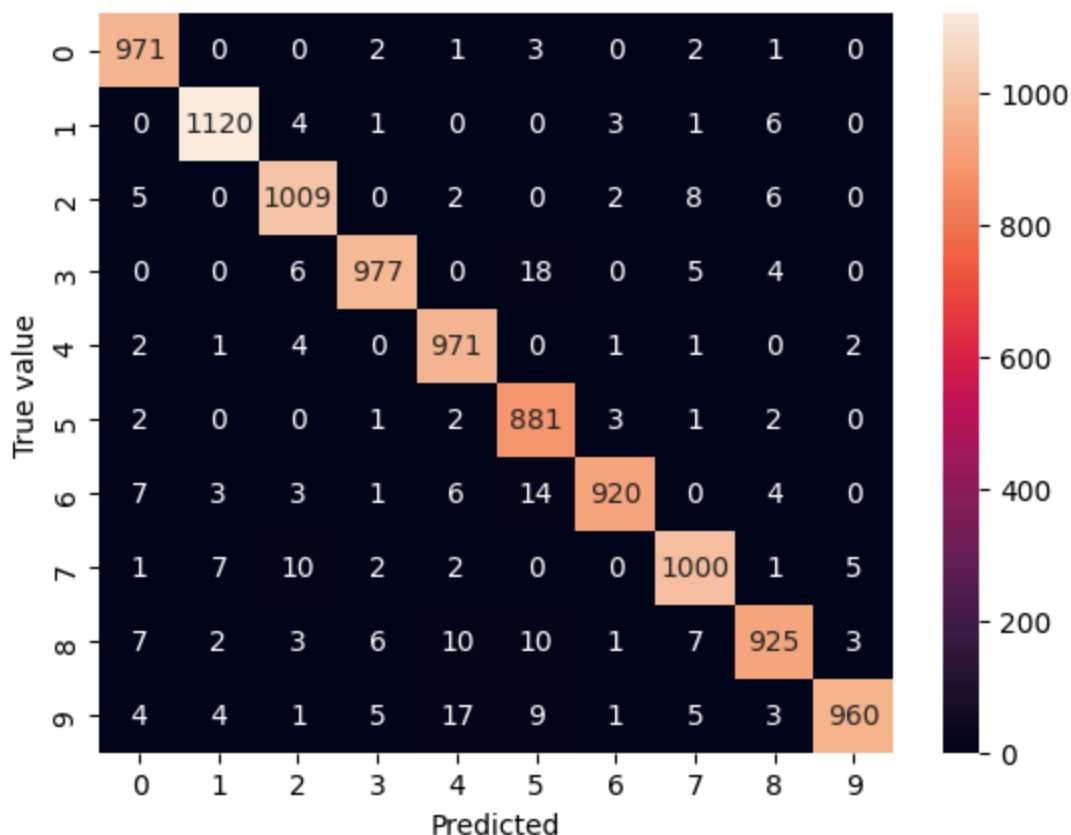
Out[66]: [0.08758094906806946, 0.9733999967575073]

In [68]: # Building a confusion metrice to evaluate he performance
 y_peddicted_Labels = [np.argmax(i) for i in model2.predict(x_test_flattened)]
 cm1 = tf.math.confusion_matrix(labels=y_test,predictions=y_peddicted_Labels)
 cm1

313/313 ————— 0s 611us/step

```
Out[68]: <tf.Tensor: shape=(10, 10), dtype=int32, numpy=
array([[ 971,    0,    0,    2,    1,    3,    0,    2,    1,    0],
       [    0, 1120,    4,    1,    0,    0,    3,    1,    6,    0],
       [    5,    0, 1009,    0,    2,    0,    2,    8,    6,    0],
       [    0,    0,    6,  977,    0,   18,    0,    5,    4,    0],
       [    2,    1,    4,    0,  971,    0,    1,    1,    0,    2],
       [    2,    0,    0,    1,    2,  881,    3,    1,    2,    0],
       [    7,    3,    3,    1,    6,   14,   920,    0,    4,    0],
       [    1,    7,   10,    2,    2,    0,    0, 1000,    1,    5],
       [    7,    2,    3,    6,   10,   10,    1,    7,   925,    3],
       [    4,    4,    1,    5,   17,    9,    1,    5,    3,   960]])>
```

```
In [70]: #Plotting the confusion matix using seaborn library for a better visual representat
sns.heatmap(cm1, annot=True, fmt='d')
plt.xlabel("Predicted")
plt.ylabel("True value")
plt.show()
```



7.1 Building the third Model using Flatten and a hidden layer

```
In [73]: #building another model with hidden layer
model3 = keras.Sequential(
    [
        #Flatten layer
        keras.layers.Flatten(input_shape=(28,28)),
```

```

keras.layers.Dense(100,activation='relu'),
keras.layers.Dense(10,activation='sigmoid')
]
)

model3.compile(optimizer='adam',
               loss='sparse_categorical_crossentropy', #we have categories of output
               metrics=['accuracy'])
model3.fit(x_train,y_train,epochs=5)

```

Epoch 1/5

C:\Anaconda3\Lib\site-packages\keras\src\layers\reshaping\flatten.py:37: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```

super().__init__(**kwargs)
1875/1875 ————— 2s 1ms/step - accuracy: 0.8753 - loss: 0.4452
Epoch 2/5
1875/1875 ————— 2s 1ms/step - accuracy: 0.9610 - loss: 0.1342
Epoch 3/5
1875/1875 ————— 2s 1ms/step - accuracy: 0.9723 - loss: 0.0919
Epoch 4/5
1875/1875 ————— 2s 1ms/step - accuracy: 0.9796 - loss: 0.0665
Epoch 5/5
1875/1875 ————— 2s 1ms/step - accuracy: 0.9850 - loss: 0.0512

```

Out[73]: <keras.src.callbacks.history.History at 0x179722307a0>

7.2 Evaluating the model

```

In [76]: # Evaluate the model for training data
         # using x_train directly without flattening
         model3.evaluate(x_train, y_train)

```

```

1875/1875 ————— 1s 752us/step - accuracy: 0.9894 - loss: 0.0381

```

Out[76]: [0.03898240998387337, 0.9888833165168762]

```

In [78]: y_preddicted_Labels = [np.argmax(i) for i in model3.predict(x_test)]
         cm3 = tf.math.confusion_matrix(labels=y_test,predictions=y_preddicted_Labels)

```

```

313/313 ————— 0s 632us/step

```

```

In [80]: #Plotting the confusion matix using seaborn library for a better visual representat
         sns.heatmap(cm3, annot=True, fmt='d')
         plt.xlabel("Predicted")
         plt.ylabel("True value")
         plt.show()

```

