In [27]:
```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np
```

1. Load the Dataset

In [29]:
```
#Load dataset
(x_train,y_train), (x_test,y_test) = keras.datasets.mnist.load_data()
```

2. Analyze and explore the dataset

In [31]:
```
#Analyze the data
x_train.shape
```

Out[31]: (60000, 28, 28)

In [32]:
```
y_train.shape
```

Out[32]: (60000,)

In [37]:
```
x_test.shape
```

Out[37]: (10000, 28, 28)

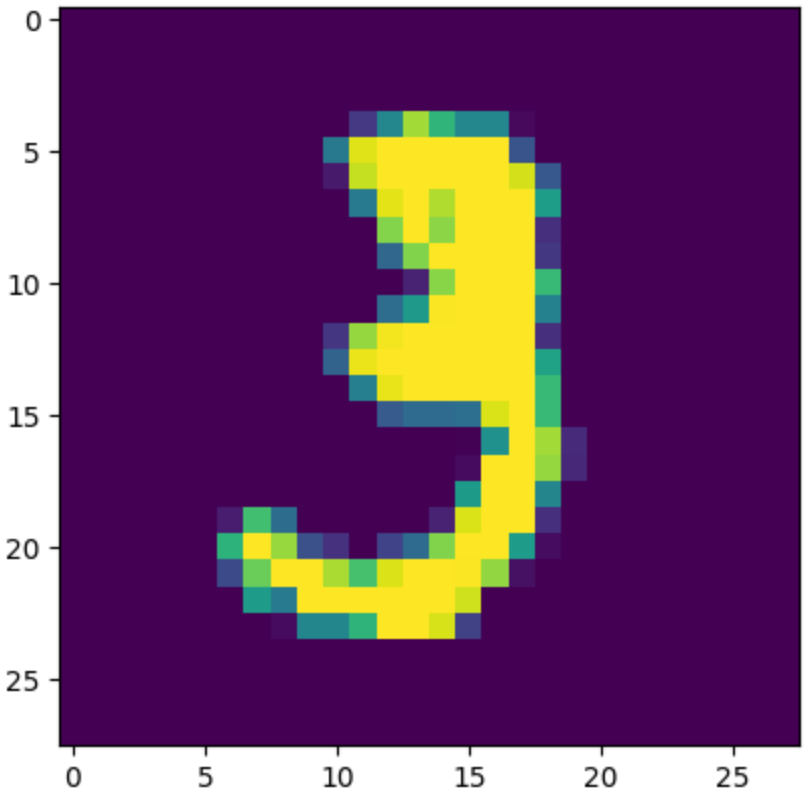
In [41]:
```
x_train[10]
```

```
Out[41]: 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,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  42, 118,
         219, 166, 118, 118,   6,   0,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0, 103, 242, 254,
         254, 254, 254, 254,  66,   0,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  18, 232, 254,
         254, 254, 254, 254, 238,  70,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0, 104, 244,
         254, 224, 254, 254, 254, 141,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0, 207,
         254, 210, 254, 254, 254,  34,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  84,
         206, 254, 254, 254, 254,  41,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          24, 209, 254, 254, 254, 171,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  91,
         137, 253, 254, 254, 254, 112,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  40, 214, 250,
         254, 254, 254, 254, 254,  34,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  81, 247, 254,
         254, 254, 254, 254, 254, 146,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0, 110, 246,
         254, 254, 254, 254, 254, 171,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  73,
          89,  89,  93, 240, 254, 171,   0,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
           0,   0,   1, 128, 254, 219,  31,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
           0,   0,   7, 254, 254, 214,  28,   0,   0,   0,   0,   0,   0,
           0,   0],
        [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
           0,   0, 138, 254, 254, 116,   0,   0,   0,   0,   0,   0,   0,
```

```
         0,   0],
       [  0,   0,   0,   0,   0,   0,  19, 177,  90,   0,   0,   0,   0,
          0,  25, 240, 254, 254,  34,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0, 164, 254, 215,  63,  36,   0,  51,
         89, 206, 254, 254, 139,   8,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,  57, 197, 254, 254, 222, 180, 241,
        254, 254, 253, 213,  11,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0, 140, 105, 254, 254, 254, 254,
        254, 254, 236,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   7, 117, 117, 165, 254,
        254, 239,  50,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
          0,   0]], dtype=uint8)
```

2.1 plot sample data to get a better visual representation

In [44]:
```
#plot sample data to get a better visual representation
plt.imshow(x_train[10])
plt.show()
```



2.2 Check the respective image label

In [47]:
```
# Check the respective image label
y_train[10]
```

Out[47]: 3

In [49]:
```
x_train.shape
```

Out[49]: (60000, 28, 28)

In [51]:
```
len(x_train)
```

Out[51]: 60000

3. Normalize the pixel data

In [54]:
```
#Normalized pixel data
x_train = x_train/255
x_test = x_test/255
```

In [56]:
```
x_train[10]
```

```
Out[56]: 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.        ,
         0.        , 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.        , 0.28627451, 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.        ],
[0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        , 0.        , 0.        ,
 0.        , 0.        , 0.        ]])
```

4. Flattening the images

In [59]:
```
x_train_flattened = x_train.reshape(len(x_train),28*28)
x_train_flattened.shape
```

Out[59]: (60000, 784)

In [61]:
```
x_test_flattened = x_test.reshape(len(x_test),28*28)
x_test_flattened.shape
```

Out[61]: (10000, 784)

5.1 Building the first Model with a single Dense Layer

In [318…
```
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 no
t pass an `input_shape`/`input_dim` argument to a layer. When using Sequential model
s, 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 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.8120 - loss: 0.7225
Epoch 2/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 950us/step - accuracy: 0.9141 - loss: 0.3109
Epoch 3/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 960us/step - accuracy: 0.9205 - loss: 0.2823
Epoch 4/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 965us/step - accuracy: 0.9258 - loss: 0.2688
Epoch 5/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 957us/step - accuracy: 0.9254 - loss: 0.2676
```

Out[318… <keras.src.callbacks.history.History at 0x1a9babd5f70>

5.2 Evaluating the model

In [320…
```
#Evaluating the model
model.evaluate(x_test_flattened,y_test)
```

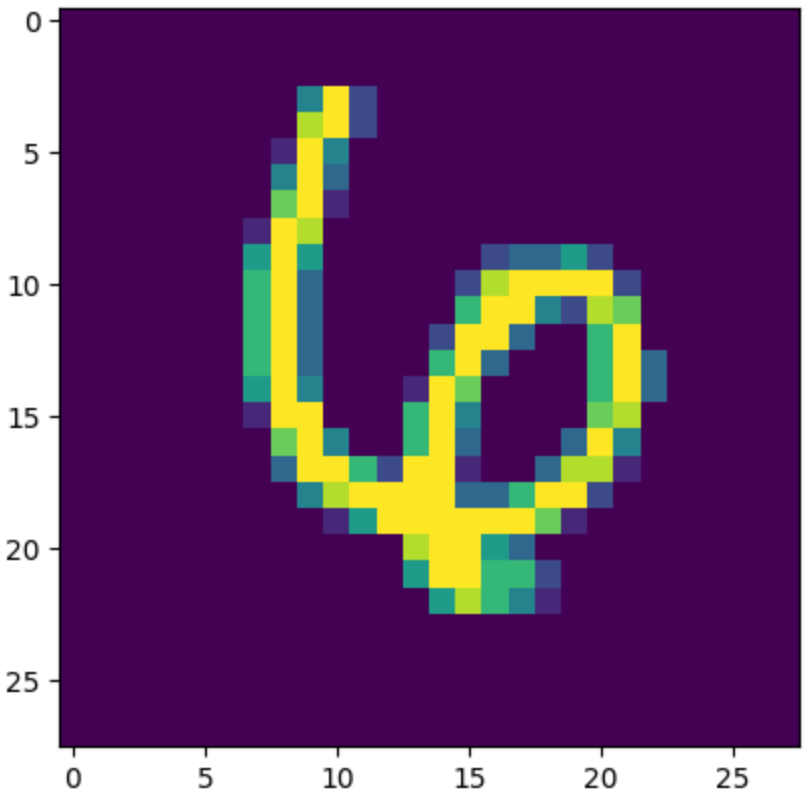
```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step - accuracy: 0.9126 - loss: 0.3079
```

Out[320… [0.27340811491012573, 0.9232000112533569]

5.3 Testing the model with a sample prediction

In [322…
```
plt.imshow(x_test[22])
```

Out[322… <matplotlib.image.AxesImage at 0x1a9baed1ee0>



In [324…
```
k = model.predict(x_test[22].reshape(1,784))
np.argmax(k)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
```

Out[324… 6

In [326…
```
y_peddicted_Labels = [np.argmax(i) for i in model.predict(x_test_flattened)]
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 676us/step
```

5.4 Building a confusion metrix to evaluate he performance

In [67]:
```
# Building a confusion metrix to evaluate he performance
cm = tf.math.confusion_matrix(labels=y_test,predictions=y_peddicted_Labels)
```

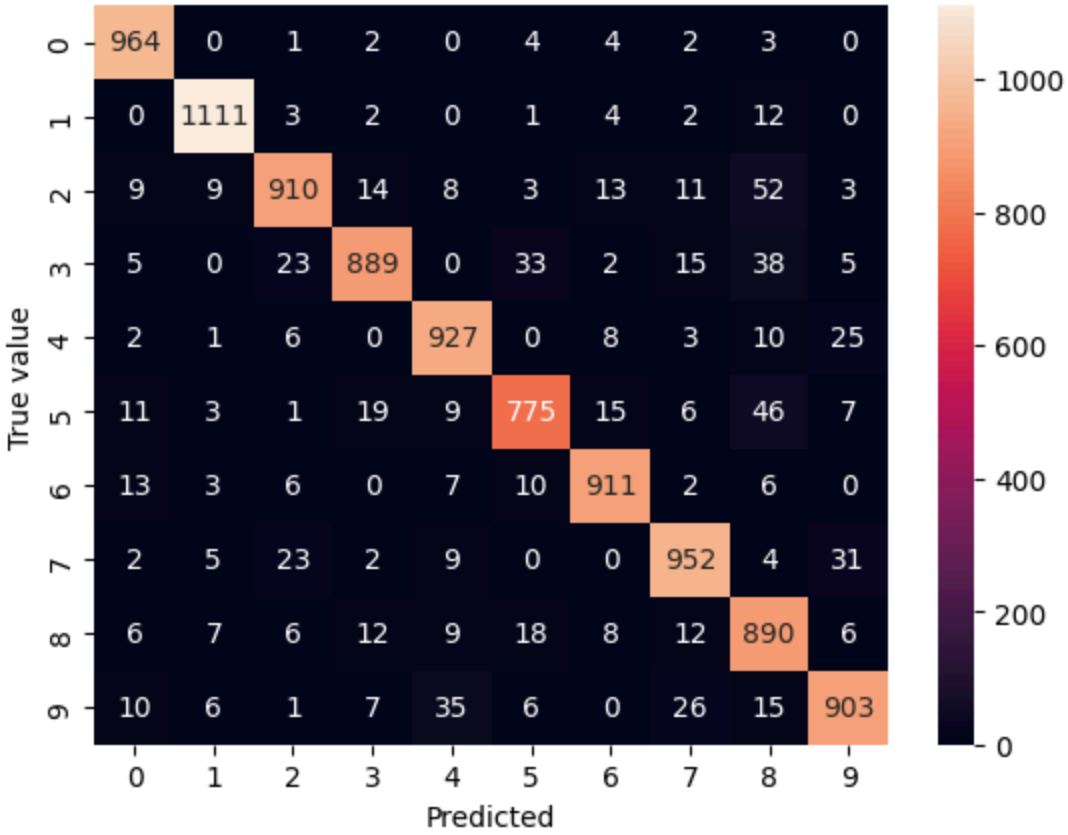
```
cm
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[67], line 2
      1 # Building a confusion metrix to evaluate he performance
----> 2 cm = tf.math.confusion_matrix(labels=y_test,predictions=y_peddicted_Labels)
      3 cm

NameError: name 'y_peddicted_Labels' is not defined
```

In [330…
```
import seaborn as sns
```

In [332…
```
#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 [334…
```
#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)
```

```
C:\Anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:93: UserWarning: Do no
t pass an `input_shape`/`input_dim` argument to a layer. When using Sequential model
s, 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 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.8695 - loss: 0.4640
Epoch 2/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9617 - loss: 0.1333
Epoch 3/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9736 - loss: 0.0902
Epoch 4/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9810 - loss: 0.0654
Epoch 5/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9844 - loss: 0.0508
```

Out[334… <keras.src.callbacks.history.History at 0x1a9bdcaa600>

6.2 Evaluating the model

In [335…
```
# evaluate model for training data
model2.evaluate(x_train_flattened, y_train)
```

```
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 984us/step - accuracy: 0.9894 - loss: 0.0377
```

Out[335… [0.038231298327445984, 0.9889333248138428]

In [338…
```
# evaluate model for testing data
model2.evaluate(x_test_flattened, y_test)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - accuracy: 0.9745 - loss: 0.0908
```

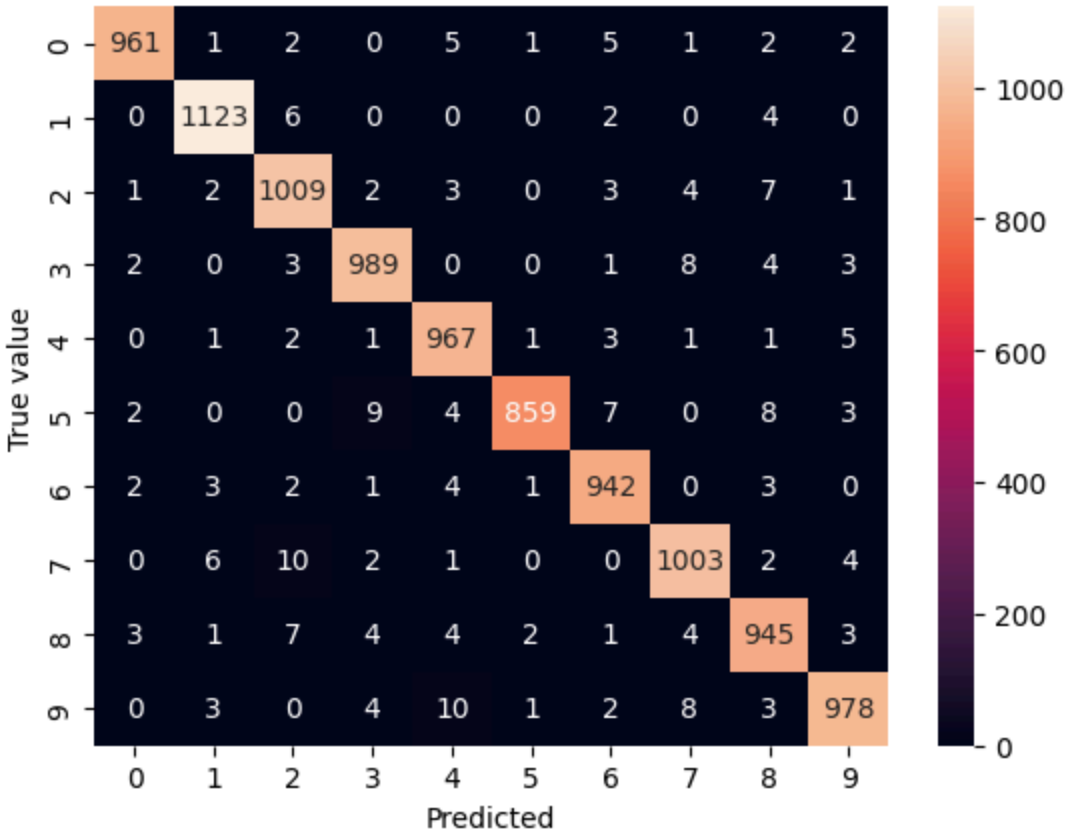
Out[338… [0.08006629347801208, 0.9775999784469604]

In [340…
```
# 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 664us/step
```

Out[340…
```
<tf.Tensor: shape=(10, 10), dtype=int32, numpy=
array([[ 961,    1,    2,    0,    5,    1,    5,    1,    2,    2],
       [   0, 1123,    6,    0,    0,    0,    2,    0,    4,    0],
       [   1,    2, 1009,    2,    3,    0,    3,    4,    7,    1],
       [   2,    0,    3,  989,    0,    0,    1,    8,    4,    3],
       [   0,    1,    2,    1,  967,    1,    3,    1,    1,    5],
       [   2,    0,    0,    9,    4,  859,    7,    0,    8,    3],
       [   2,    3,    2,    1,    4,    1,  942,    0,    3,    0],
       [   0,    6,   10,    2,    1,    0,    0, 1003,    2,    4],
       [   3,    1,    7,    4,    4,    2,    1,    4,  945,    3],
       [   0,    3,    0,    4,   10,    1,    2,    8,    3,  978]])>
```

In [342…
```
#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 [344…
```
#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)
```

```
C:\Anaconda3\Lib\site-packages\keras\src\layers\reshaping\flatten.py:37: UserWarnin
g: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequenti
al models, prefer using an `Input(shape)` object as the first layer in the model ins
tead.
  super().__init__(**kwargs)
Epoch 1/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.8676 - loss: 0.4742
Epoch 2/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9606 - loss: 0.1377
Epoch 3/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9724 - loss: 0.0906
Epoch 4/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9809 - loss: 0.0642
Epoch 5/5
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step - accuracy: 0.9840 - loss: 0.0535
```

Out[344… <keras.src.callbacks.history.History at 0x1a9be213950>

7.2 Evaluating the model

In [346…
```
# Evaluate the model for training data
# using x_train derectly without flattening
model3.evaluate(x_train, y_train)
```

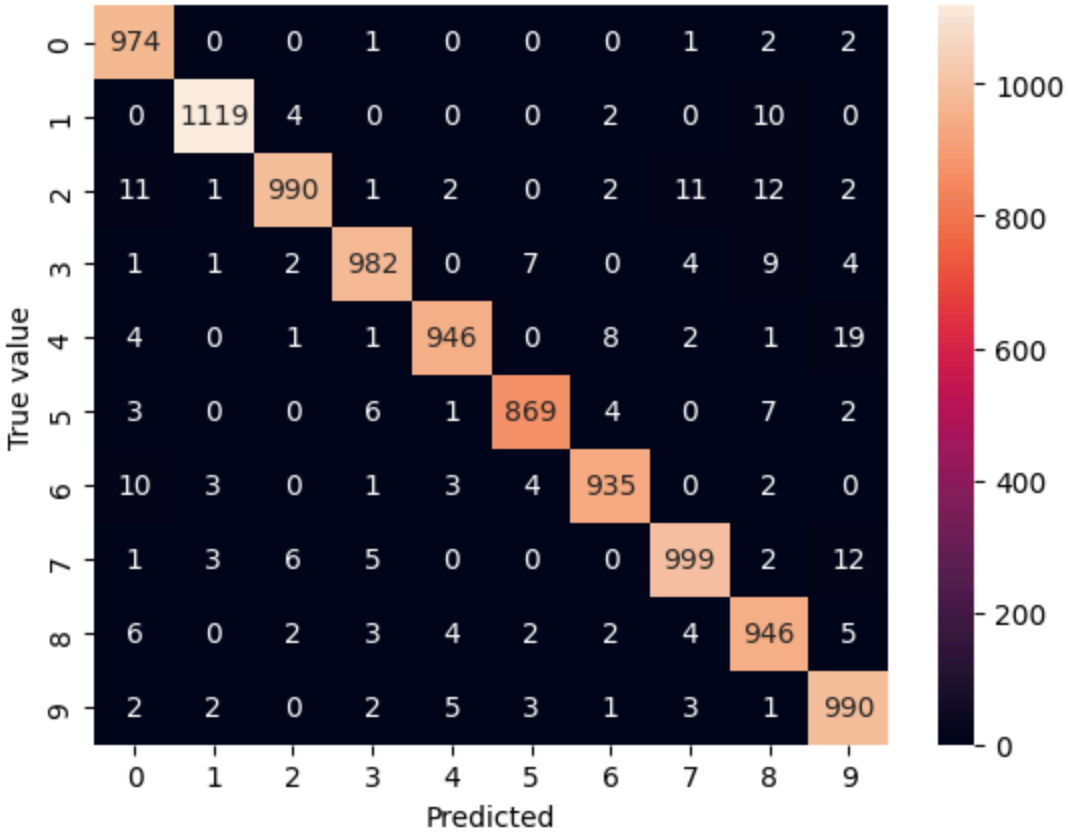
```
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 2s 973us/step - accuracy: 0.9868 - loss: 0.0458
```

Out[346… [0.04632463678717613, 0.9859333038330078]

In [348…
```
y_peddicted_Labels = [np.argmax(i) for i in model3.predict(x_test)]
cm3 = tf.math.confusion_matrix(labels=y_test,predictions=y_peddicted_Labels)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 644us/step
```

In [350…
```
#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()
```


True value
Predicted
0 974 0 0 1 0 0 0 1 2 2
1 0 1119 4 0 0 0 2 0 10 0
2 11 1 990 1 2 0 2 11 12 2
3 1 1 2 982 0 7 0 4 9 4
4 4 0 1 1 946 0 8 2 1 19
5 3 0 0 6 1 869 4 0 7 2
6 10 3 0 1 3 4 935 0 2 0
7 1 3 6 5 0 0 0 999 2 12
8 6 0 2 3 4 2 2 4 946 5
9 2 2 0 2 5 3 1 3 1 990
0 1 2 3 4 5 6 7 8 9
1000
800
600
400
200
0

In [ ]: