

COURSE OUTCOME-4

PROGRAM NO-1

Aim: Programs on feedforward network to classify any standard dataset available in the public domain

```
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense
from tensorflow.keras.optimizers import SGD
from matplotlib import pyplot as plt

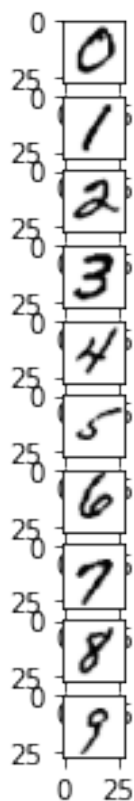
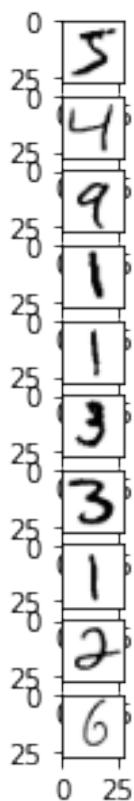
(x_train,y_train),(x_valid,y_valid) = mnist.load_data()

x_train.shape
(60000, 28, 28)

y_train.shape
(60000,)

y_train[0:12]
array([5, 0, 4, 1, 9, 2, 1, 3, 1, 4, 3, 5], dtype=uint8)

plt.figure(figsize=(5,5))
for k in range(20):
    plt.subplot(10,2,k+1)
    plt.imshow(x_train[k],cmap='Greys')
    plt.axis('on')
plt.show()
```

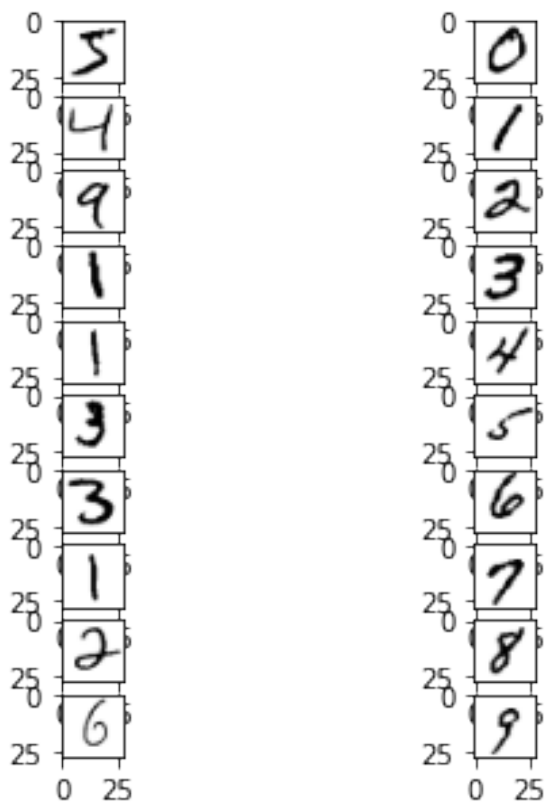


```
plt.figure(figsize=(5,5))
for k in range(20):
    plt.subplot(10,2,k+1)
    plt.imshow(x_train[k],cmap='Greys')
    plt.axis('off')
plt.show()
```

5
4
9
1
1
3
3
1
2
6

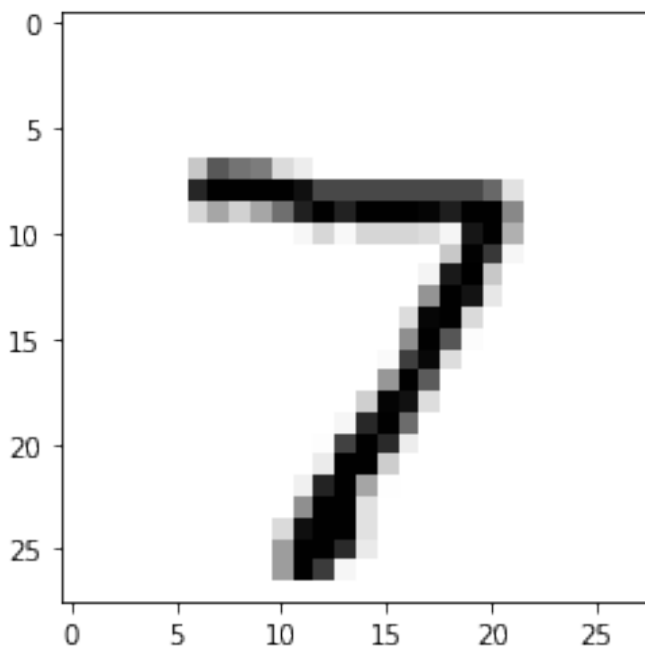
0
1
2
3
4
5
6
7
8
9

```
plt.figure(figsize=(5,5))
for k in range(20):
    plt.subplot(10,2,k+1)
    plt.imshow(x_train[k],cmap='Greys')
    plt.axis('on')
plt.show()
```



```
plt.imshow(x_valid[0], cmap='Greys')
```

```
<matplotlib.image.AxesImage at 0x7fd83619e610>
```



```
y_valid.shape
```

(10000,)

x_valid[0]

```
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,  0,  0,  0,
        0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  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, 222, 254, 254, 254, 254, 241,
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, 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,  0,  0]
```

[illegible]

```

0,      19, 221, 254, 166,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
3,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      203, 254, 219,  35,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
38,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      254, 254,  77,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
224,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, 31,
0,      254, 115,  1,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
254,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, 133,
0,      254,  52,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
254,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, 61, 242,
0,      254,  52,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
254,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, 121, 254,
0,      219,  40,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,      0,  0],
207,      [  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, 121, 254,
0,      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,  0], dtype=uint8)

```

y_valid[0]

7

preprocess data

[illegible]

0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.32941177, 0.7254902 , 0.62352943,
0.5921569 , 0.23529412, 0.14117648, 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.87058824, 0.99607843, 0.99607843, 0.99607843, 0.99607843,
0.94509804, 0.7764706 , 0.7764706 , 0.7764706 , 0.7764706 ,
0.7764706 , 0.7764706 , 0.7764706 , 0.7764706 , 0.6666667 ,
0.20392157, 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.2627451 , 0.44705883,
0.28235295, 0.44705883, 0.6392157 , 0.8901961 , 0.99607843,
0.88235295, 0.99607843, 0.99607843, 0.99607843, 0.98039216,
0.8980392 , 0.99607843, 0.99607843, 0.54901963, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.06666667, 0.25882354, 0.05490196, 0.2627451 ,
0.2627451 , 0.2627451 , 0.23137255, 0.08235294, 0.9254902 ,
0.99607843, 0.41568628, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.3254902 , 0.99215686, 0.81960785, 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. , 0.08627451, 0.9137255 ,
1. , 0.3254902 , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.5058824 , 0.99607843, 0.93333334, 0.17254902,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,

0. , 0. , 0. , 0.23137255, 0.9764706 ,
0.99607843, 0.24313726, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.52156866, 0.99607843, 0.73333335, 0.01960784,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.03529412, 0.8039216 ,
0.972549 , 0.22745098, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.49411765, 0.99607843, 0.7137255 , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.29411766, 0.9843137 ,
0.9411765 , 0.22352941, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.07450981, 0.8666667 , 0.99607843, 0.6509804 , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.01176471, 0.79607844, 0.99607843,
0.85882354, 0.13725491, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.14901961, 0.99607843, 0.99607843, 0.3019608 , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.12156863, 0.8784314 , 0.99607843,
0.4509804 , 0.00392157, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,

[illegible]

0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.01176471,	0.07058824,	0.07058824,	
0.07058824,	0.49411765,	0.53333336,	0.6862745 ,	0.10196079,	
0.6509804 ,	1.	, 0.96862745,	0.49803922,	0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.11764706,	0.14117648,	0.36862746,	0.6039216 ,	
0.6666667 ,	0.99215686,	0.99215686,	0.99215686,	0.99215686,	
0.99215686,	0.88235295,	0.6745098 ,	0.99215686,	0.9490196 ,	
0.7647059 ,	0.2509804 ,	0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.19215687,	0.93333334,	
0.99215686,	0.99215686,	0.99215686,	0.99215686,	0.99215686,	
0.99215686,	0.99215686,	0.99215686,	0.9843137 ,	0.3647059 ,	
0.32156864,	0.32156864,	0.21960784,	0.15294118,	0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.07058824,	0.85882354,	0.99215686,	0.99215686,	
0.99215686,	0.99215686,	0.99215686,	0.7764706 ,	0.7137255 ,	
0.96862745,	0.94509804,	0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.3137255 ,	0.6117647 ,	0.41960785,	0.99215686,	0.99215686,	
0.8039216 ,	0.04313726,	0.	, 0.16862746,	0.6039216 ,	
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.05490196,	
0.00392157,	0.6039216 ,	0.99215686,	0.3529412 ,	0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.54509807,	
0.99215686,	0.74509805,	0.00784314,	0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.04313726,	0.74509805,	0.99215686,	
0.27450982,	0.	, 0.	, 0.	, 0.	,
0.	, 0.	, 0.	, 0.	, 0.	,

0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.13725491,	0.94509804,	0.88235295,	0.627451	
0.42352942,	0.00392157,	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.31764707,	0.9411765	0.99215686,	0.99215686,	0.46666667,	
0.09803922,	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	0.1764706
0.7294118	0.99215686,	0.99215686,	0.5882353	0.10588235,	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.0627451	0.3647059	
0.9882353	0.99215686,	0.73333335,	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.9764706	0.99215686,	
0.9764706	0.2509804	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.18039216,	0.50980395,	
0.7176471	0.99215686,	0.99215686,	0.8117647	0.00784314,	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.15294118,	
0.5803922	0.8980392	0.99215686,	0.99215686,	0.99215686,	
0.98039216,	0.7137255	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.09411765,	0.44705883,	0.8666667	0.99215686,	0.99215686,	
0.99215686,	0.99215686,	0.7882353	0.30588236,	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.	0.	0.	0.	
0.	0.09019608,	0.25882354,	0.8352941	0.99215686,	
0.99215686,	0.99215686,	0.99215686,	0.7764706	0.31764707,	
0.00784314,	0.	0.	0.	0.	

[illegible]

0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0.04313726 ,
0.5882353 , 0.99215686 , 0.7921569 , 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. , 0.14509805 , 0.9843137 , 0.9843137 ,
0.99215686 , 0.41960785 , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0.08235294 ,
0.77254903 , 0.9843137 , 0.9843137 , 0.99215686 , 0.41960785 ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.43137255 , 0.74509805 , 0.9843137 , 0.9843137 ,
0.9843137 , 0.99215686 , 0.6627451 , 0.42745098 , 0.24313726 ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0.99215686 ,
0.9843137 , 0.9843137 , 0.9843137 , 0.9843137 , 0.99215686 ,
0.9843137 , 0.9843137 , 0.8627451 , 0.2 , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.7137255 , 1. , 0.99215686 , 0.99215686 ,
0.99215686 , 0.99215686 , 0.91764706 , 0.87058824 , 0.99215686 ,
0.99215686 , 0.99215686 , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.24705882 , 0.8666667 ,
0.99215686 , 0.9843137 , 0.9843137 , 0.9843137 , 0.5764706 ,
0.3019608 , 0.24313726 , 0.5019608 , 0.9843137 , 0.9843137 ,
0.4117647 , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,

0.1254902 , 0.90588236, 0.9843137 , 0.99215686, 0.9843137 ,
0.8627451 , 0.5372549 , 0.03921569, 0. , 0. ,
0.12156863, 0.9019608 , 0.9843137 , 0.9529412 , 0.44313726,
0.01960784, 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.14509805, 0.9843137 ,
0.9843137 , 0.99215686, 0.7372549 , 0.07843138, 0. ,
0. , 0. , 0. , 0. , 0.42745098,
0.9843137 , 0.99215686, 0.9843137 , 0.13725491, 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.14509805, 0.9843137 , 0.9843137 , 0.7882353 ,
0.11764706, 0. , 0. , 0. , 0. ,
0. , 0. , 0.12156863, 0.78431374, 0.99215686,
0.9843137 , 0.13725491, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0.14509805,
0.99215686, 0.99215686, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.1254902 , 0.7921569 , 1. , 0.99215686, 0.6431373 ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0.54901963, 0.9843137 , 0.9843137 ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.42745098, 0.9843137 ,
0.99215686, 0.9843137 , 0.13725491, 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0.8509804 , 0.9843137 , 0.9843137 , 0. , 0. ,
0. , 0. , 0. , 0. , 0.08235294,
0.24705882, 0.90588236, 0.9843137 , 0.99215686, 0.9019608 ,
0.11764706, 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0.8509804 , 0.9843137 ,
0.9843137 , 0. , 0. , 0. ,
0. , 0. , 0.5647059 , 0.9843137 , 0.9843137 ,
0.9843137 , 0.8666667 , 0.23921569, 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0.8509804 , 0.9843137 , 0.9843137 , 0. ,
0. , 0. , 0. , 0. , 0.7137255 ,
0.8666667 , 0.9843137 , 0.9843137 , 0.9843137 , 0.7058824 ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0.85490197,
0.99215686, 0.99215686, 0.28627452, 0.28627452, 0.89411765,
0.99215686, 0.99215686, 1. , 0.99215686, 0.99215686,
0.99215686, 0.99215686, 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,
0. , 0. , 0. , 0. , 0. ,


```
model = Sequential()
```

```
model.add(Dense(64, activation='sigmoid', input_shape=(784,)))    #64
neurons in the hidden layer 784 inputs
```

```
#final layer
```

```
model.add(Dense(10, activation='softmax'))
```

```
model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	50240
dense_1 (Dense)	(None, 10)	650

```
=====  
Total params: 50,890
```

```
Trainable params: 50,890
```

```
Non-trainable params: 0  
=====
```

```
(64*784) #wi xi total weights at input
```

```
50176
```

```
(64*784)+64
```

```
50240
```

```
(10*64)
```

```
640
```

```
(10*64)+10
```

```
650
```

```
((10*64)+10) + ((64*784)+64)
```

```
50890
```

```
model.compile(loss='mean_squared_error', optimizer=SGD(learning_rate=0.03), metrics=['accuracy'])
```

```
history= model.fit(x_train,y_train,batch_size=128,epochs=75,verbose=1)
```

```
#overbose=0 will show you nothing
```

```
#verbose=1 will show you an animated progress bar like this:
```

```
#progress bar
```

```
#overbose=2 will just mention the number of epoch like this:
```

```
Epoch 1/75
```

```
469/469 [=====] - 2s 3ms/step - loss: 0.0593
```

```
- accuracy: 0.6446
Epoch 2/75
469/469 [=====] - 2s 3ms/step - loss: 0.0579
- accuracy: 0.6593
Epoch 3/75
469/469 [=====] - 2s 3ms/step - loss: 0.0565
- accuracy: 0.6744
Epoch 4/75
469/469 [=====] - 1s 3ms/step - loss: 0.0552
- accuracy: 0.6880
Epoch 5/75
469/469 [=====] - 2s 3ms/step - loss: 0.0539
- accuracy: 0.7019
Epoch 6/75
469/469 [=====] - 1s 3ms/step - loss: 0.0526
- accuracy: 0.7151
Epoch 7/75
469/469 [=====] - 1s 3ms/step - loss: 0.0514
- accuracy: 0.7260
Epoch 8/75
469/469 [=====] - 2s 3ms/step - loss: 0.0503
- accuracy: 0.7379
Epoch 9/75
469/469 [=====] - 2s 3ms/step - loss: 0.0492
- accuracy: 0.7463
Epoch 10/75
469/469 [=====] - 1s 3ms/step - loss: 0.0481
- accuracy: 0.7545
Epoch 11/75
469/469 [=====] - 2s 3ms/step - loss: 0.0470
- accuracy: 0.7629
Epoch 12/75
469/469 [=====] - 2s 3ms/step - loss: 0.0460
- accuracy: 0.7695
Epoch 13/75
469/469 [=====] - 2s 3ms/step - loss: 0.0451
- accuracy: 0.7768
Epoch 14/75
469/469 [=====] - 2s 3ms/step - loss: 0.0441
- accuracy: 0.7839
Epoch 15/75
469/469 [=====] - 2s 3ms/step - loss: 0.0433
- accuracy: 0.7900
Epoch 16/75
469/469 [=====] - 1s 3ms/step - loss: 0.0424
- accuracy: 0.7962
Epoch 17/75
469/469 [=====] - 1s 3ms/step - loss: 0.0416
- accuracy: 0.8018
Epoch 18/75
```

469/469 [=====] - 2s 3ms/step - loss: 0.0407
- accuracy: 0.8069
Epoch 19/75
469/469 [=====] - 1s 3ms/step - loss: 0.0400
- accuracy: 0.8123
Epoch 20/75
469/469 [=====] - 1s 3ms/step - loss: 0.0392
- accuracy: 0.8166
Epoch 21/75
469/469 [=====] - 1s 3ms/step - loss: 0.0385
- accuracy: 0.8205
Epoch 22/75
469/469 [=====] - 2s 3ms/step - loss: 0.0378
- accuracy: 0.8244
Epoch 23/75
469/469 [=====] - 1s 3ms/step - loss: 0.0371
- accuracy: 0.8277
Epoch 24/75
469/469 [=====] - 1s 3ms/step - loss: 0.0365
- accuracy: 0.8307
Epoch 25/75
469/469 [=====] - 2s 3ms/step - loss: 0.0358
- accuracy: 0.8335
Epoch 26/75
469/469 [=====] - 2s 3ms/step - loss: 0.0352
- accuracy: 0.8358
Epoch 27/75
469/469 [=====] - 1s 3ms/step - loss: 0.0346
- accuracy: 0.8384
Epoch 28/75
469/469 [=====] - 2s 3ms/step - loss: 0.0341
- accuracy: 0.8405
Epoch 29/75
469/469 [=====] - 2s 3ms/step - loss: 0.0335
- accuracy: 0.8425
Epoch 30/75
469/469 [=====] - 2s 3ms/step - loss: 0.0330
- accuracy: 0.8442
Epoch 31/75
469/469 [=====] - 1s 3ms/step - loss: 0.0325
- accuracy: 0.8461
Epoch 32/75
469/469 [=====] - 2s 3ms/step - loss: 0.0320
- accuracy: 0.8476
Epoch 33/75
469/469 [=====] - 1s 3ms/step - loss: 0.0316
- accuracy: 0.8487
Epoch 34/75
469/469 [=====] - 2s 3ms/step - loss: 0.0311
- accuracy: 0.8500

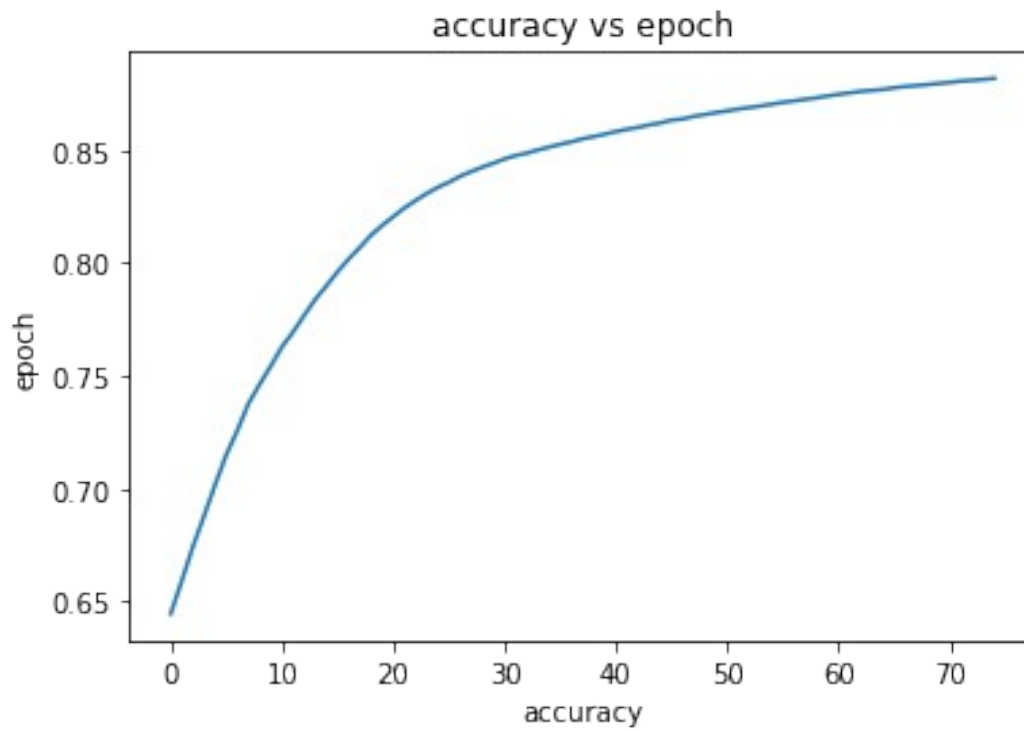
Epoch 35/75
469/469 [=====] - 2s 3ms/step - loss: 0.0307
- accuracy: 0.8513
Epoch 36/75
469/469 [=====] - 2s 3ms/step - loss: 0.0303
- accuracy: 0.8526
Epoch 37/75
469/469 [=====] - 1s 3ms/step - loss: 0.0299
- accuracy: 0.8536
Epoch 38/75
469/469 [=====] - 1s 3ms/step - loss: 0.0295
- accuracy: 0.8550
Epoch 39/75
469/469 [=====] - 1s 3ms/step - loss: 0.0291
- accuracy: 0.8559
Epoch 40/75
469/469 [=====] - 1s 3ms/step - loss: 0.0288
- accuracy: 0.8571
Epoch 41/75
469/469 [=====] - 1s 3ms/step - loss: 0.0284
- accuracy: 0.8582
Epoch 42/75
469/469 [=====] - 2s 3ms/step - loss: 0.0281
- accuracy: 0.8592
Epoch 43/75
469/469 [=====] - 1s 3ms/step - loss: 0.0278
- accuracy: 0.8601
Epoch 44/75
469/469 [=====] - 2s 3ms/step - loss: 0.0275
- accuracy: 0.8612
Epoch 45/75
469/469 [=====] - 1s 3ms/step - loss: 0.0272
- accuracy: 0.8620
Epoch 46/75
469/469 [=====] - 1s 3ms/step - loss: 0.0269
- accuracy: 0.8633
Epoch 47/75
469/469 [=====] - 2s 3ms/step - loss: 0.0266
- accuracy: 0.8638
Epoch 48/75
469/469 [=====] - 1s 3ms/step - loss: 0.0263
- accuracy: 0.8649
Epoch 49/75
469/469 [=====] - 2s 3ms/step - loss: 0.0261
- accuracy: 0.8658
Epoch 50/75
469/469 [=====] - 2s 3ms/step - loss: 0.0258
- accuracy: 0.8666
Epoch 51/75
469/469 [=====] - 1s 3ms/step - loss: 0.0256

- accuracy: 0.8674
Epoch 52/75
469/469 [=====] - 1s 3ms/step - loss: 0.0253
- accuracy: 0.8682
Epoch 53/75
469/469 [=====] - 1s 3ms/step - loss: 0.0251
- accuracy: 0.8688
Epoch 54/75
469/469 [=====] - 2s 3ms/step - loss: 0.0249
- accuracy: 0.8696
Epoch 55/75
469/469 [=====] - 2s 3ms/step - loss: 0.0247
- accuracy: 0.8703
Epoch 56/75
469/469 [=====] - 2s 3ms/step - loss: 0.0244
- accuracy: 0.8712
Epoch 57/75
469/469 [=====] - 1s 3ms/step - loss: 0.0242
- accuracy: 0.8718
Epoch 58/75
469/469 [=====] - 1s 3ms/step - loss: 0.0240
- accuracy: 0.8725
Epoch 59/75
469/469 [=====] - 2s 3ms/step - loss: 0.0238
- accuracy: 0.8731
Epoch 60/75
469/469 [=====] - 1s 3ms/step - loss: 0.0237
- accuracy: 0.8740
Epoch 61/75
469/469 [=====] - 2s 3ms/step - loss: 0.0235
- accuracy: 0.8747
Epoch 62/75
469/469 [=====] - 2s 3ms/step - loss: 0.0233
- accuracy: 0.8753
Epoch 63/75
469/469 [=====] - 1s 3ms/step - loss: 0.0231
- accuracy: 0.8760
Epoch 64/75
469/469 [=====] - 1s 3ms/step - loss: 0.0230
- accuracy: 0.8764
Epoch 65/75
469/469 [=====] - 1s 3ms/step - loss: 0.0228
- accuracy: 0.8768
Epoch 66/75
469/469 [=====] - 1s 3ms/step - loss: 0.0227
- accuracy: 0.8777
Epoch 67/75
469/469 [=====] - 1s 3ms/step - loss: 0.0225
- accuracy: 0.8781
Epoch 68/75

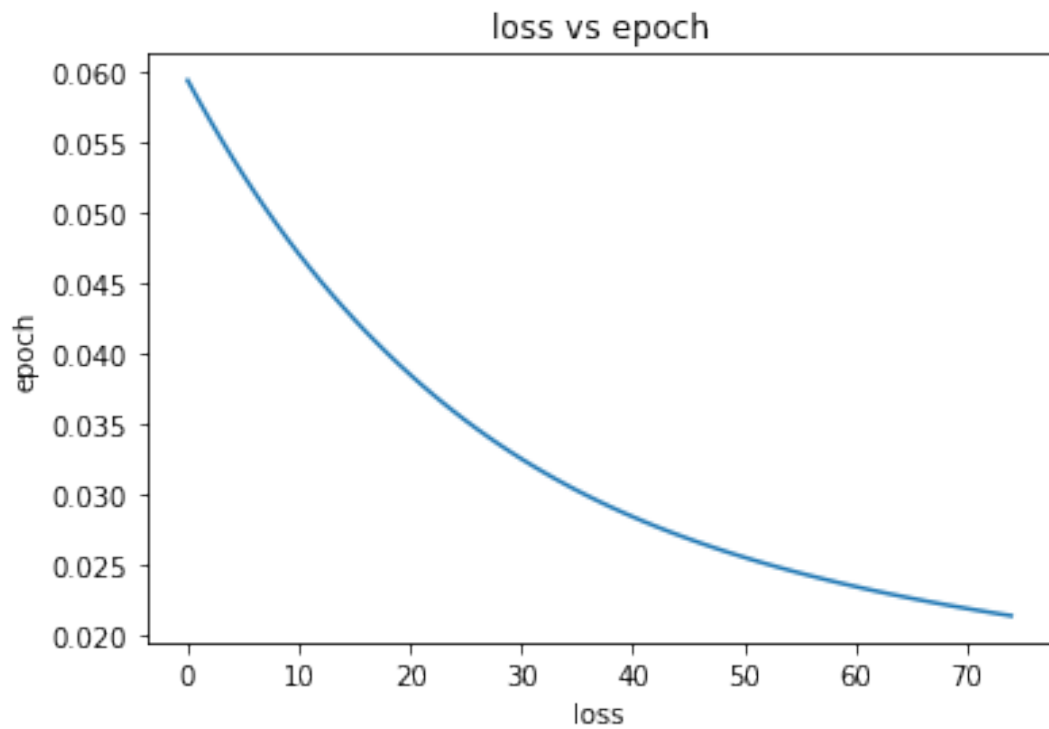
```
469/469 [=====] - 1s 3ms/step - loss: 0.0224
- accuracy: 0.8786
Epoch 69/75
469/469 [=====] - 2s 3ms/step - loss: 0.0222
- accuracy: 0.8790
Epoch 70/75
469/469 [=====] - 1s 3ms/step - loss: 0.0221
- accuracy: 0.8795
Epoch 71/75
469/469 [=====] - 1s 3ms/step - loss: 0.0219
- accuracy: 0.8800
Epoch 72/75
469/469 [=====] - 2s 3ms/step - loss: 0.0218
- accuracy: 0.8806
Epoch 73/75
469/469 [=====] - 1s 3ms/step - loss: 0.0217
- accuracy: 0.8809
Epoch 74/75
469/469 [=====] - 2s 3ms/step - loss: 0.0215
- accuracy: 0.8813
Epoch 75/75
469/469 [=====] - 1s 3ms/step - loss: 0.0214
- accuracy: 0.8818
```

```
plt.plot(history.history['accuracy'])
plt.title('accuracy vs epoch')
plt.xlabel('accuracy')
plt.ylabel('epoch')

Text(0, 0.5, 'epoch')
```



```
plt.plot(history.history['loss'])  
plt.title('loss vs epoch')  
plt.xlabel('loss')  
plt.ylabel('epoch')  
Text(0, 0.5, 'epoch')
```

Result: The program is executed successfully and obtained the output.

PROGRAM NO-2

Aim: Programs on convolutional neural network to classify images from any standard dataset in the public domain.

```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import classification_report

(xtrain, ytrain), (xtest, ytest) = datasets.cifar10.load_data()

Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-
python.tar.gz
170500096/170498071 [=====] - 6s 0us/step
170508288/170498071 [=====] - 6s 0us/step

xtrain.shape

(50000, 32, 32, 3)

xtest.shape

(10000, 32, 32, 3)

classes =
['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'shi
p', 'truck']

def plot_sample(x, y, index):
    plt.figure(figsize=(14, 2))
    plt.imshow(x[index])
    plt.imshow(y[index])

plot_sample(xtrain, ytrain, 1)

-----
-----
TypeError                                Traceback (most recent call
last)
<ipython-input-24-024740e61cba> in <module>()
----> 1 plot_sample(xtrain, ytrain, 1)

<ipython-input-23-dd56c6c969e7> in plot_sample(x, y, index)
      2     plt.figure(figsize=(14, 2))
      3     plt.imshow(x[index])
----> 4     plt.imshow(y[index])
      5

/usr/local/lib/python3.7/dist-packages/matplotlib/pyplot.py in
```

```

imshow(X, cmap, norm, aspect, interpolation, alpha, vmin, vmax,
origin, extent, shape, filternorm, filterrad, imlim, resample, url,
data, **kwargs)
    2649         filternorm=filternorm, filterrad=filterrad,
imlim=imlim,
    2650         resample=resample, url=url, **({"data": data} if data
is not
-> 2651         None else {}), **kwargs)
    2652     sci(__ret)
    2653     return __ret

```

```

/usr/local/lib/python3.7/dist-packages/matplotlib/__init__.py in
inner(ax, data, *args, **kwargs)
    1563     def inner(ax, *args, data=None, **kwargs):
    1564         if data is None:
-> 1565             return func(ax, *map(sanitize_sequence, args),
**kwargs)
    1566
    1567         bound = new_sig.bind(ax, *args, **kwargs)

```

```

/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/deprecation.py
in wrapper(*args, **kwargs)
    356         f"%(removal)s. If any parameter follows
{name!r}, they "
    357         f"should be pass as keyword, not
positionally.")
--> 358         return func(*args, **kwargs)
    359
    360     return wrapper

```

```

/usr/local/lib/python3.7/dist-packages/matplotlib/cbook/deprecation.py
in wrapper(*args, **kwargs)
    356         f"%(removal)s. If any parameter follows
{name!r}, they "
    357         f"should be pass as keyword, not
positionally.")
--> 358         return func(*args, **kwargs)
    359
    360     return wrapper

```

```

/usr/local/lib/python3.7/dist-packages/matplotlib/axes/_axes.py in
imshow(self, X, cmap, norm, aspect, interpolation, alpha, vmin, vmax,
origin, extent, shape, filternorm, filterrad, imlim, resample, url,
**kwargs)
    5624         resample=resample, **kwargs)
    5625
-> 5626     im.set_data(X)
    5627     im.set_alpha(alpha)
    5628     if im.get_clip_path() is None:

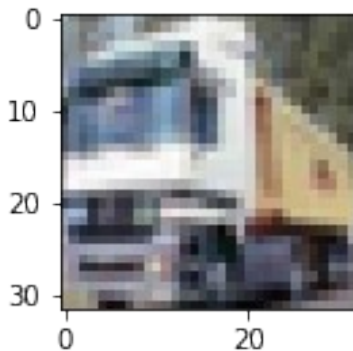
```

```

/usr/local/lib/python3.7/dist-packages/matplotlib/image.py in
set_data(self, A)
    697             or self._A.ndim == 3 and self._A.shape[-1] in
[3, 4]):
    698             raise TypeError("Invalid shape {} for image data"
--> 699                             .format(self._A.shape))
    700
    701             if self._A.ndim == 3:

```

TypeError: Invalid shape (1,) for image data



```

#Normalize
xtrain = xtrain/255
xtest = xtest/255

#model
cnn = models.Sequential([
    #feature extraction
    layers.Conv2D(filters=32,activation='relu',kernel_size =
(3,3),input_shape=(32,32,3)),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(filters=64,activation='relu',kernel_size =
(3,3),input_shape = (32,32,3)),
    layers.MaxPooling2D((2,2)),

    #classification
    layers.Flatten(),
    layers.Dense(64,activation='relu'),
    layers.Dense(10,activation='softmax')

])

cnn.compile(optimizer='adam',loss='sparse_categorical_crossentropy',me
trics=['accuracy'])

cnn.fit(xtrain,ytrain,epochs=20)

Epoch 1/20
1563/1563 [=====] - 42s 27ms/step - loss:

```

2.3028 - accuracy: 0.0963
Epoch 2/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0993
Epoch 3/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0958
Epoch 4/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0975
Epoch 5/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0967
Epoch 6/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3027 - accuracy: 0.0974
Epoch 7/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0972
Epoch 8/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0977
Epoch 9/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0978
Epoch 10/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3027 - accuracy: 0.0979
Epoch 11/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0972
Epoch 12/20
1563/1563 [=====] - 42s 27ms/step - loss:
2.3028 - accuracy: 0.0973
Epoch 13/20
1563/1563 [=====] - 43s 27ms/step - loss:
2.3028 - accuracy: 0.0977
Epoch 14/20
1563/1563 [=====] - 43s 28ms/step - loss:
2.3028 - accuracy: 0.0984
Epoch 15/20
1563/1563 [=====] - 43s 28ms/step - loss:
2.3028 - accuracy: 0.0995
Epoch 16/20
1563/1563 [=====] - 43s 28ms/step - loss:
2.3028 - accuracy: 0.0981
Epoch 17/20
1563/1563 [=====] - 43s 28ms/step - loss:
2.3028 - accuracy: 0.0982
Epoch 18/20

```
1563/1563 [=====] - 43s 28ms/step - loss: 2.3028 - accuracy: 0.0982
```

```
Epoch 19/20
```

```
1563/1563 [=====] - 43s 28ms/step - loss: 2.3028 - accuracy: 0.0996
```

```
Epoch 20/20
```

```
1563/1563 [=====] - 43s 28ms/step - loss: 2.3028 - accuracy: 0.0966
```

```
<keras.callbacks.History at 0x7f9e5c739b50>
```

```
ypred = cnn.predict(xtest)
```

```
cnn.evaluate(xtest,ytest)
```

```
313/313 [=====] - 3s 9ms/step - loss: 2.3027 - accuracy: 0.1000
```

```
[2.3026859760284424, 0.10000000149011612]
```

```
ytest=ytest.reshape(-1,)
```

```
ypred=cnn.predict(xtest)
```

```
yclasses=[np.argmax(element) for element in ypred]
```

```
print('classification report:\n',classification_report(ytest,yclasses))
```

```
classification report:
```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	1000
1	0.10	1.00	0.18	1000
2	0.00	0.00	0.00	1000
3	0.00	0.00	0.00	1000
4	0.00	0.00	0.00	1000
5	0.00	0.00	0.00	1000
6	0.00	0.00	0.00	1000
7	0.00	0.00	0.00	1000
8	0.00	0.00	0.00	1000
9	0.00	0.00	0.00	1000
accuracy			0.10	10000
macro avg	0.01	0.10	0.02	10000
weighted avg	0.01	0.10	0.02	10000

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
```

```
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Result: The program is executed successfully and obtained the output.