ASSIGNMENT NO. 1

```
from sklearn.datasets import load boston
import pandas as pd
boston dataset = load boston()
df = pd.DataFrame(boston dataset.data,
columns=boston dataset.feature names)
df['MEDV'] = boston dataset.target
df.head(n=10)
                                                                      In [3]:
# If load boston does not work then download the data and use this.
# Data :
https://github.com/afnan47/sem8/blob/master/DL/1 boston housing.csv
import pandas as pd
df = pd.read csv("./1 boston housing.csv")
                                                                      In [4]:
from sklearn.model selection import train test split
X = df.loc[:, df.columns != 'MEDV']
y = df.loc[:, df.columns == 'MEDV']
X train, X test, y train, y test = train test split(X, y, test size=0.3,
random state=123)
                                                                      In [5]:
\textbf{from} \text{ sklearn.preprocessing } \textbf{import} \text{ MinMaxScaler}
mms = MinMaxScaler()
mms.fit(X train)
X train = mms.transform(X train)
X test = mms.transform(X test)
                                                                      In [1]:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
model = Sequential()
model.add(Dense(128, input shape=(13, ), activation='relu',
name='dense 1'))
model.add(Dense(64, activation='relu', name='dense_2'))
model.add(Dense(1, activation='linear', name='dense output'))
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
model.summary()
Model: "sequential"
Layer (type)
                           Output Shape
______
dense 1 (Dense)
                            (None, 128)
                                                      1792
dense 2 (Dense)
                           (None, 64)
                                                      8256
 dense output (Dense) (None, 1)
                                                      65
```

```
-----
```

```
Total params: 10,113
Trainable params: 10,113
Non-trainable params: 0
```

```
In [ ]:
history = model.fit(X train, y train, epochs=100, validation split=0.05,
verbose = 1)
Epoch 1/100
ae: 32.0408 - val loss: 104.8761 - val mae: 6.1343
11/11 [============== ] - Os 9ms/step - loss: 291.9155 - mae
: 13.9797 - val loss: 149.5561 - val mae: 11.4423
Epoch 3/100
: 10.3968 - val loss: 141.8171 - val mae: 7.9483
Epoch 4/100
7.0836 - val loss: 96.4421 - val mae: 8.3894
Epoch 5/100
: 5.8493 - val loss: 79.1745 - val mae: 5.6716
Epoch 6/100
11/11 [=============== ] - Os 13ms/step - loss: 59.8653 - mae
: 5.6803 - val_loss: 81.4188 - val_mae: 5.8136
Epoch 7/100
5.3080 - val loss: 78.1150 - val_mae: 6.1632
Epoch 8/100
5.0945 - val_loss: 78.3047 - val_mae: 6.4755
Epoch 9/100
5.2586 - val loss: 78.7134 - val mae: 6.3377
Epoch 10/100
5.3718 - val loss: 85.3209 - val mae: 7.5740
Epoch 11/100
6.0167 - val_loss: 82.1899 - val_mae: 5.8459
Epoch 12/100
5.9333 - val loss: 90.0579 - val mae: 6.0229
Epoch 13/100
5.7201 - val loss: 93.0269 - val mae: 6.0567
Epoch 14/100
5.3231 - val loss: 78.0659 - val mae: 6.2727
Epoch 15/100
11/11 [============= ] - Os 11ms/step - loss: 49.6804 - mae
: 4.9658 - val loss: 78.2121 - val mae: 6.2786
Epoch 16/100
: 5.1608 - val loss: 82.2059 - val mae: 6.0243
```

```
Epoch 17/100
: 5.0943 - val loss: 79.5624 - val mae: 6.7917
Epoch 18/100
4.8631 - val loss: 79.4000 - val mae: 6.9262
Epoch 19/100
4.8788 - val loss: 78.2341 - val mae: 6.6031
Epoch 20/100
: 4.8531 - val_loss: 79.5777 - val_mae: 6.2096
Epoch 21/100
11/11 [============== ] - Os 15ms/step - loss: 46.8095 - mae
: 4.8446 - val loss: 79.9989 - val mae: 6.2106
Epoch 22/100
: 4.8957 - val loss: 80.0767 - val mae: 6.3410
Epoch 23/100
4.7125 - val loss: 79.3820 - val mae: 6.3287
Epoch 24/100
4.6794 - val loss: 78.1009 - val mae: 6.8739
Epoch 25/100
4.8287 - val loss: 77.1064 - val mae: 6.9487
Epoch 26/100
4.8219 - val loss: 80.3456 - val mae: 7.5219
Epoch 27/100
4.8070 - val loss: 86.8667 - val mae: 7.9910
Epoch 28/100
5.2916 - val loss: 75.9413 - val mae: 6.9428
Epoch 29/100
4.7075 - val loss: 75.8774 - val mae: 6.8408
Epoch 30/100
4.5150 - val_loss: 74.4587 - val_mae: 6.8040
Epoch 31/100
4.6436 - val_loss: 72.5272 - val_mae: 6.0201
Epoch 32/100
4.7250 - val loss: 73.3913 - val mae: 6.0527
Epoch 33/100
4.5334 - val loss: 70.9002 - val mae: 6.6792
Epoch 34/100
4.9500 - val loss: 70.4410 - val mae: 6.3134
Epoch 35/100
4.7071 - val loss: 76.1223 - val mae: 5.9119
```

```
Epoch 36/100
4.7664 - val loss: 78.8820 - val mae: 5.6082
Epoch 37/100
4.4803 - val loss: 69.7008 - val mae: 6.2753
Epoch 38/100
4.4467 - val loss: 70.4070 - val mae: 5.9936
Epoch 39/100
4.5365 - val_loss: 70.5524 - val_mae: 5.7211
Epoch 40/100
4.3651 - val loss: 68.0985 - val mae: 6.1247
Epoch 41/100
4.6153 - val loss: 67.4054 - val mae: 6.3753
Epoch 42/100
4.6629 - val loss: 67.4899 - val mae: 5.8294
Epoch 43/100
11/11 [============== ] - Os 4ms/step - loss: 40.0755 - mae:
4.5632 - val loss: 68.8983 - val mae: 5.8097
Epoch 44/100
4.5411 - val loss: 67.7507 - val mae: 6.1112
Epoch 45/100
4.8104 - val loss: 76.0111 - val mae: 7.6458
Epoch 46/100
4.8151 - val loss: 67.7236 - val mae: 5.6180
Epoch 47/100
4.1907 - val loss: 65.1950 - val mae: 5.4492
Epoch 48/100
4.2764 - val loss: 73.0951 - val mae: 5.5137
Epoch 49/100
4.4734 - val_loss: 65.3500 - val_mae: 5.4734
Epoch 50/100
4.4038 - val_loss: 65.8660 - val_mae: 6.4395
Epoch 51/100
4.3774 - val loss: 66.5157 - val mae: 5.5489
Epoch 52/100
4.3058 - val loss: 65.4602 - val mae: 5.6216
Epoch 53/100
4.3144 - val loss: 71.0284 - val mae: 5.6592
Epoch 54/100
4.3036 - val loss: 79.4032 - val mae: 5.6828
```

```
Epoch 55/100
4.1692 - val loss: 63.7029 - val mae: 6.1306
Epoch 56/100
4.3432 - val loss: 64.8605 - val mae: 5.7787
Epoch 57/100
4.2143 - val loss: 73.1095 - val mae: 5.7776
Epoch 58/100
4.0968 - val_loss: 75.7989 - val_mae: 6.0117
Epoch 59/100
4.4993 - val loss: 69.9205 - val mae: 5.8598
Epoch 60/100
4.3774 - val loss: 93.1340 - val mae: 6.6789
Epoch 61/100
4.1797 - val loss: 69.6372 - val mae: 6.9278
Epoch 62/100
5.2795 - val loss: 74.5363 - val mae: 5.8979
Epoch 63/100
4.6395 - val loss: 67.6870 - val mae: 5.7321
Epoch 64/100
4.4874 - val loss: 63.1919 - val mae: 6.0185
Epoch 65/100
4.1380 - val loss: 75.4116 - val mae: 5.7737
Epoch 66/100
4.3020 - val loss: 65.2549 - val mae: 5.6731
Epoch 67/100
3.9988 - val loss: 65.9374 - val mae: 6.0587
Epoch 68/100
4.0822 - val_loss: 70.9584 - val_mae: 5.9610
Epoch 69/100
4.0980 - val_loss: 65.5629 - val_mae: 6.0606
Epoch 70/100
3.9024 - val loss: 66.6761 - val mae: 5.7830
Epoch 71/100
4.1027 - val loss: 73.0866 - val mae: 5.8113
Epoch 72/100
4.1465 - val loss: 65.9663 - val mae: 5.8200
Epoch 73/100
4.0037 - val loss: 68.6681 - val mae: 5.7642
```

```
Epoch 74/100
3.9230 - val loss: 70.9759 - val mae: 5.7254
Epoch 75/100
3.7621 - val loss: 65.1627 - val mae: 5.7805
Epoch 76/100
3.9348 - val loss: 63.4590 - val mae: 5.9799
Epoch 77/100
4.1665 - val_loss: 71.6206 - val_mae: 5.7315
Epoch 78/100
3.9052 - val loss: 63.1969 - val mae: 5.9108
Epoch 79/100
3.9858 - val loss: 79.6432 - val mae: 6.1192
Epoch 80/100
4.0720 - val loss: 64.5131 - val mae: 5.7942
Epoch 81/100
11/11 [============== ] - Os 3ms/step - loss: 27.6364 - mae:
3.8092 - val loss: 65.6751 - val_mae: 5.5210
Epoch 82/100
3.9231 - val loss: 91.4888 - val mae: 6.3524
Epoch 83/100
4.8559 - val loss: 60.2526 - val mae: 5.8334
Epoch 84/100
4.8038 - val loss: 68.2171 - val mae: 5.4533
Epoch 85/100
3.9874 - val loss: 67.0612 - val mae: 5.5345
Epoch 86/100
3.8464 - val loss: 63.5904 - val mae: 5.8538
Epoch 87/100
3.9001 - val_loss: 79.7395 - val_mae: 5.8449
Epoch 88/100
4.0870 - val_loss: 64.1248 - val_mae: 6.0386
Epoch 89/100
3.9004 - val loss: 64.7652 - val mae: 5.6717
Epoch 90/100
3.7857 - val loss: 73.6284 - val mae: 5.6817
Epoch 91/100
3.6840 - val loss: 61.2618 - val mae: 6.2671
Epoch 92/100
4.7214 - val loss: 70.1923 - val mae: 5.4056
```

```
Epoch 93/100
4.1516 - val loss: 59.7963 - val mae: 6.0707
Epoch 94/100
4.0330 - val_loss: 57.3263 - val_mae: 5.6396
Epoch 95/100
3.9198 - val loss: 77.2184 - val mae: 5.6756
Epoch 96/100
4.0007 - val_loss: 63.6341 - val_mae: 6.7858
Epoch 97/100
4.1860 - val loss: 69.4769 - val mae: 5.6059
Epoch 98/100
3.8078 - val loss: 65.4580 - val mae: 5.5055
Epoch 99/100
3.6395 - val loss: 67.9779 - val mae: 5.6516
Epoch 100/100
3.7184 - val loss: 63.8970 - val mae: 5.7290
                                     In [ ]:
mse nn, mae nn = model.evaluate(X test, y test)
print('Mean squared error on test data: ', mse nn)
print('Mean absolute error on test data: ', mae_nn)
.8497
Mean squared error on test data: 25.959447860717773
Mean absolute error on test data: 3.8496510982513428
```

ASSIGNMENT NO.2

```
from tensorflow.keras.datasets import imdb
                                                                In [15]:
(train data, train label), (test data, test label) =
imdb.load_data(num words = 10000)
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-da
tasets/imdb.npz
In [24]:
import numpy as np
def vectorize sequences(sequences, dimensions = 10000):
 results = np.zeros((len(sequences), dimensions))
 for i, sequences in enumerate(sequences):
   results[i, sequences] = 1
 return results
x_train = vectorize_sequences(train_data)
y train = vectorize sequences(test data)
                                                                In [25]:
y train = np.asarray(train label).astype('float32')
y_test = np.asarray(test_label).astype('float32')
                                                                In [31]:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
                                                                In [19]:
model = Sequential()
model.add(Dense(16, input_shape=(10000, ), activation = "relu"))
model.add(Dense(16, activation = "relu"))
model.add(Dense(1, activation = "sigmoid"))
                                                                In [32]:
model.compile(optimizer='adam', loss = 'mse', metrics = ['accuracy'])
                                                                In [22]:
model.summary()
Model: "sequential"
Layer (type)
                         Output Shape
______
dense (Dense)
                          (None, 16)
                                                  160016
                 (None, 16)
dense 1 (Dense)
                                                  272
```

Total params: 160,305 Trainable params: 160,305 Non-trainable params: 0

In [33]: history = model.fit(x_train, y_train, validation_split = 0.3, epochs = 20, verbose = 1, batch size = 512) Epoch 1/20 35/35 [===============] - 2s 39ms/step - loss: 0.0041 - accu racy: 0.9960 - val_loss: 0.1162 - val_accuracy: 0.8652 Epoch 2/20 racy: 0.9959 - val loss: 0.1171 - val accuracy: 0.8648 Epoch 3/20 35/35 [=============] - 1s 32ms/step - loss: 0.0043 - accu racy: 0.9958 - val loss: 0.1192 - val accuracy: 0.8636 35/35 [==============] - 1s 31ms/step - loss: 0.0042 - accu racy: 0.9959 - val loss: 0.1210 - val accuracy: 0.8619 Epoch 5/20 racy: 0.9960 - val loss: 0.1208 - val accuracy: 0.8628 Epoch 6/20 racy: 0.9959 - val loss: 0.1210 - val accuracy: 0.8619 Epoch 7/20 35/35 [=============] - 2s 47ms/step - loss: 0.0040 - accu racy: 0.9961 - val_loss: 0.1213 - val_accuracy: 0.8621 Epoch 8/20 35/35 [==============] - 1s 31ms/step - loss: 0.0041 - accu racy: 0.9960 - val loss: 0.1214 - val accuracy: 0.8620 Epoch 9/20 racy: 0.9961 - val loss: 0.1204 - val_accuracy: 0.8655 Epoch 10/20 35/35 [============] - 1s 32ms/step - loss: 0.0041 - accu racy: 0.9961 - val loss: 0.1215 - val accuracy: 0.8633 Epoch 11/20 racy: 0.9961 - val loss: 0.1224 - val accuracy: 0.8623 Epoch 12/20 35/35 [============] - 1s 32ms/step - loss: 0.0039 - accu racy: 0.9961 - val loss: 0.1223 - val accuracy: 0.8617 Epoch 13/20 35/35 [============] - 1s 35ms/step - loss: 0.0039 - accu racy: 0.9961 - val loss: 0.1223 - val accuracy: 0.8613 Epoch 14/20 racy: 0.9961 - val loss: 0.1223 - val accuracy: 0.8616 Epoch 15/20 35/35 [============] - 1s 31ms/step - loss: 0.0039 - accu racy: 0.9961 - val loss: 0.1223 - val accuracy: 0.8613

ASSIGNMENT NO.3

```
from tensorflow.keras.datasets import fashion mnist
                                                              In [38]:
(train x, train y), (test x, test y) = fashion mnist.load data()
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-da
tasets/train-labels-idx1-ubyte.gz
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-da
tasets/train-images-idx3-ubyte.gz
26421880/26421880 [============= ] - Os Ous/step
{\tt Downloading \ data \ from \ https://storage.googleapis.com/tensorflow/tf-keras-da}
tasets/t10k-labels-idx1-ubyte.gz
5148/5148 [============== ] - Os Ous/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-da
tasets/t10k-images-idx3-ubyte.gz
In [ ]:
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, MaxPooling2D, Conv2D
                                                              In [50]:
model = Sequential()
                                                              In [51]:
model.add(Conv2D(filters=64, kernel size=(3,3), activation='relu', input shape
=(28, 28, 1))
# Adding maxpooling layer to get max value within a matrix
model.add(MaxPooling2D(pool size=(2,2)))
model.add(Flatten())
model.add(Dense(128, activation = "relu"))
model.add(Dense(10, activation = "softmax"))
                                                              In [52]:
model.summary()
Model: "sequential 2"
 Layer (type)
                         Output Shape
                                                 Param #
______
 flatten 1 (Flatten)
                         (None, 784)
 dense 8 (Dense)
                         (None, 128)
                                                 100480
 dense 9 (Dense)
                         (None, 10)
                                                 1290
```

Total params: 101,770

Trainable params: 101,770 Non-trainable params: 0

```
In [56]:
model.compile(optimizer = 'adam', loss = 'sparse categorical crossentropy',
metrics = ['accuracy'])
                                                        In [85]:
model.fit(train x.astype(np.float32), train y.astype(np.float32), epochs =
5, validation split = 0.2)
Epoch 1/5
ccuracy: 0.8302 - val loss: 0.5287 - val accuracy: 0.8273
ccuracy: 0.8298 - val loss: 0.5376 - val accuracy: 0.8243
Epoch 3/5
1500/1500 [============== ] - 7s 5ms/step - loss: 0.4774 - a
ccuracy: 0.8342 - val loss: 0.5451 - val accuracy: 0.8282
Epoch 4/5
ccuracy: 0.8361 - val loss: 0.5717 - val accuracy: 0.8299
Epoch 5/5
1500/1500 [============== ] - 7s 5ms/step - loss: 0.4753 - a
ccuracy: 0.8363 - val loss: 0.5278 - val accuracy: 0.8255
                                                        Out[85]:
<keras.callbacks.History at 0x7fbcee0aceb0>
                                                        In [86]:
loss, acc = model.evaluate(test x, test y)
uracy: 0.8171
                                                        In [87]:
labels = ['t_shirt', 'trouser', 'pullover', 'dress', 'coat', 'sandal',
'shirt', 'sneaker', 'bag', 'ankle_boots']
                                                        In [88]:
predictions = model.predict(test x[:1])
1/1 [=======] - 0s 73ms/step
                                                        In [90]:
import numpy as np
                                                        In [91]:
label = labels[np.argmax(predictions)]
                                                        In [93]:
import matplotlib.pyplot as plt
print(label)
plt.imshow(test x[:1][0])
```

ankle_boots

Out[93]:

<function matplotlib.pyplot.show(close=None, block=None)>

