```
In [ ]:
        import pandas as pd
In [7]:
        import numpy as np
        data = pd.read csv(r"C:\Users\jitendra\Desktop\suhani\DATASET\1 boston housing.csv")
In [3]: | 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 [4]: | from sklearn.preprocessing import MinMaxScaler
        mms = MinMaxScaler()
        mms.fit(X_train)
        X train = mms.transform(X train)
        X_test = mms.transform(X_test)
In [5]: 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()
```

WARNING:tensorflow:From C:\Users\jitendra\anaconda3\Anaconda\Lib\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please u se tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

WARNING:tensorflow:From C:\Users\jitendra\anaconda3\Anaconda\Lib\site-packages\keras\src \backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.ge t_default_graph instead.

WARNING:tensorflow:From C:\Users\jitendra\anaconda3\Anaconda\Lib\site-packages\keras\src \optimizers__init__.py:309: The name tf.train.Optimizer is deprecated. Please use tf.co mpat.v1.train.Optimizer instead.

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|---|---|-------------|
| dense_1 (Dense) | (None, 128) | 1792 |
| dense_2 (Dense) | (None, 64) | 8256 |
| dense_output (Dense) | (None, 1) | 65 |
| ======================================= | ======================================= | =========== |

Total params: 10113 (39.50 KB)
Trainable params: 10113 (39.50 KB)
Non-trainable params: 0 (0.00 Byte)

In [8]: data.head(n=10)

Out[8]:

| | crim | zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | b | Istat | MEDV |
|---|---------|------|-------|------|-------|-------|-------|--------|-----|-----|---------|--------|-------|------|
| 0 | 0.00632 | 18.0 | 2.31 | 0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1 | 296 | 15.3 | 396.90 | 4.98 | 24.0 |
| 1 | 0.02731 | 0.0 | 7.07 | 0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.90 | 9.14 | 21.6 |
| 2 | 0.02729 | 0.0 | 7.07 | 0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.03 | 34.7 |
| 3 | 0.03237 | 0.0 | 2.18 | 0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.94 | 33.4 |
| 4 | 0.06905 | 0.0 | 2.18 | 0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.90 | 5.33 | 36.2 |
| 5 | 0.02985 | 0.0 | 2.18 | 0 | 0.458 | 6.430 | 58.7 | 6.0622 | 3 | 222 | 18.7 | 394.12 | 5.21 | 28.7 |
| 6 | 0.08829 | 12.5 | 7.87 | 0 | 0.524 | 6.012 | 66.6 | 5.5605 | 5 | 311 | 15.2 | 395.60 | 12.43 | 22.9 |
| 7 | 0.14455 | 12.5 | 7.87 | 0 | 0.524 | 6.172 | 96.1 | 5.9505 | 5 | 311 | 15.2 | 396.90 | 19.15 | 27.1 |
| 8 | 0.21124 | 12.5 | 7.87 | 0 | 0.524 | 5.631 | 100.0 | 6.0821 | 5 | 311 | 15.2 | 386.63 | 29.93 | 16.5 |
| 9 | 0.17004 | 12.5 | 7.87 | 0 | 0.524 | 6.004 | 85.9 | 6.5921 | 5 | 311 | 15.2 | 386.71 | 17.10 | 18.9 |

In [9]: print(data.shape)

(506, 14)

In [10]: data.isnull().sum()

Out[10]: crim

0 zn 0 indus 0 chas 0 0 nox 0 rm0 age dis rad tax ptratio lstat 0 MEDV dtype: int64

In [11]: data.describe()

Out[11]:

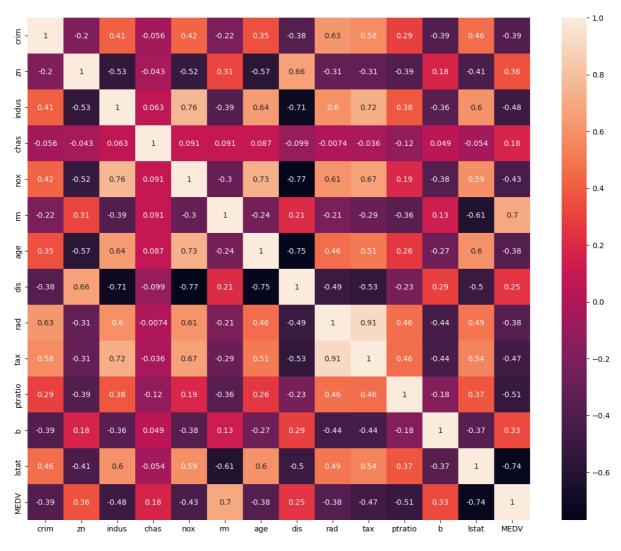
| | crim | zn | indus | chas | nox | rm | age | dis | | |
|-------|------------|------------|------------|------------|------------|------------|------------|------------|--------|--|
| count | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.000000 | 506.00 | |
| mean | 3.613524 | 11.363636 | 11.136779 | 0.069170 | 0.554695 | 6.284634 | 68.574901 | 3.795043 | 9.54 | |
| std | 8.601545 | 23.322453 | 6.860353 | 0.253994 | 0.115878 | 0.702617 | 28.148861 | 2.105710 | 8.70 | |
| min | 0.006320 | 0.000000 | 0.460000 | 0.000000 | 0.385000 | 3.561000 | 2.900000 | 1.129600 | 1.00 | |
| 25% | 0.082045 | 0.000000 | 5.190000 | 0.000000 | 0.449000 | 5.885500 | 45.025000 | 2.100175 | 4.00 | |
| 50% | 0.256510 | 0.000000 | 9.690000 | 0.000000 | 0.538000 | 6.208500 | 77.500000 | 3.207450 | 5.00 | |
| 75% | 3.677083 | 12.500000 | 18.100000 | 0.000000 | 0.624000 | 6.623500 | 94.075000 | 5.188425 | 24.00 | |
| max | 88.976200 | 100.000000 | 27.740000 | 1.000000 | 0.871000 | 8.780000 | 100.000000 | 12.126500 | 24.00 | |
| _ | | | | | | | | | | |

```
Data columns (total 14 columns):
 #
     Column
             Non-Null Count Dtype
     ____
              -----
 0
     crim
             506 non-null
                             float64
 1
    zn
             506 non-null
                             float64
 2
             506 non-null
                             float64
    indus
 3
             506 non-null
                             int64
    chas
 4
             506 non-null
                             float64
    nox
 5
             506 non-null
                             float64
    rm
 6
              506 non-null
                             float64
     age
 7
              506 non-null
                             float64
     dis
 8
              506 non-null
                             int64
    rad
 9
             506 non-null
                             int64
    tax
                             float64
 10
    ptratio 506 non-null
 11
    b
             506 non-null
                             float64
 12 lstat
              506 non-null
                             float64
 13 MEDV
              506 non-null
                             float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

```
In [15]: correlation = data.corr()
```

```
In [16]: import matplotlib.pyplot as plt
import seaborn as sns
fig,axes = plt.subplots(figsize=(15,12))
sns.heatmap(correlation,square = True,annot = True)
```

```
Out[16]: <Axes: >
```



```
In [17]: mean = X_train.mean(axis=0)
    std = X_train.std(axis=0)
    X_train = (X_train - mean) / std
    X_test = (X_test - mean) / std
```

```
In [18]: from sklearn.linear_model import LinearRegression
    regressor = LinearRegression()
    #Fitting the model
    regressor.fit(X_train,y_train)
```

Out[18]:
v LinearRegression
LinearRegression()

```
In [19]: y_pred = regressor.predict(X_test)
# Predicting RMSE the Test set results
from sklearn.metrics import mean_squared_error
rmse = (np.sqrt(mean_squared_error(y_test, y_pred)))
print(rmse)
```

5.329714327288869

```
In [20]: from sklearn.metrics import r2_score
    r2 = r2_score(y_test, y_pred)
    print(r2)
```

0.6485645742370704

```
In [21]: from sklearn.preprocessing import StandardScaler
    sc = StandardScaler()
    X_train = sc.fit_transform(X_train)
    X_test = sc.transform(X_test)
```

```
In [22]: import keras
    from keras.layers import Dense, Activation,Dropout
    from keras.models import Sequential
    model = Sequential()
    model.add(Dense(128,activation = 'relu',input_dim =13))
    model.add(Dense(64,activation = 'relu'))
    model.add(Dense(32,activation = 'relu'))
    model.add(Dense(16,activation = 'relu'))
    model.add(Dense(11))
```

```
In [27]: from plotly.subplots import make_subplots
import plotly.graph_objects as go
```

In [29]: history = model.fit(X_train, y_train, epochs=100, validation_split=0.05, verbose = 1)

Epoch 1/100

WARNING:tensorflow:From C:\Users\jitendra\anaconda3\Anaconda\Lib\site-packages\keras\src \utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use t f.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Users\jitendra\anaconda3\Anaconda\Lib\site-packages\keras\src \engine\base_layer_utils.py:384: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing eagerly outside functions instead.

```
- val loss: 596.2977 - val mae: 22.5246
Epoch 2/100
val loss: 514.0519 - val mae: 20.7619
Epoch 3/100
val_loss: 356.5651 - val_mae: 16.8917
Epoch 4/100
val_loss: 139.6987 - val_mae: 9.6914
Epoch 5/100
l_loss: 61.2518 - val_mae: 6.0208
Epoch 6/100
1_loss: 38.7943 - val_mae: 4.9534
Epoch 7/100
l_loss: 28.8961 - val_mae: 4.3492
Epoch 8/100
l loss: 17.2308 - val mae: 3.4260
Epoch 9/100
11/11 [===========] - 0s 31ms/step - loss: 25.0295 - mae: 3.7171 - va
l loss: 15.3707 - val mae: 3.1138
Epoch 10/100
l_loss: 14.1067 - val_mae: 3.0348
Epoch 11/100
1_loss: 13.5427 - val_mae: 2.8788
Epoch 12/100
l_loss: 11.9552 - val_mae: 2.8914
Epoch 13/100
l_loss: 11.3451 - val_mae: 2.7676
Epoch 14/100
l_loss: 10.6373 - val_mae: 2.6149
Epoch 15/100
l_loss: 10.0033 - val_mae: 2.6655
Epoch 16/100
l loss: 9.2314 - val mae: 2.4704
Epoch 17/100
l loss: 8.7567 - val mae: 2.4011
Epoch 18/100
1_loss: 8.1658 - val_mae: 2.2796
Epoch 19/100
l_loss: 7.8507 - val_mae: 2.2792
Epoch 20/100
l_loss: 7.3493 - val_mae: 2.1279
```

```
Epoch 21/100
l_loss: 8.0241 - val_mae: 2.4960
Epoch 22/100
l loss: 6.9930 - val mae: 2.2019
Epoch 23/100
l_loss: 8.0183 - val_mae: 2.4032
Epoch 24/100
l_loss: 6.9163 - val_mae: 2.1917
Epoch 25/100
l loss: 7.7265 - val mae: 2.3141
Epoch 26/100
l loss: 7.1624 - val mae: 2.1988
Epoch 27/100
l loss: 7.5602 - val mae: 2.2642
Epoch 28/100
l loss: 7.7257 - val mae: 2.3023
Epoch 29/100
loss: 7.1177 - val mae: 2.1562
Epoch 30/100
l_loss: 7.9539 - val_mae: 2.2689
Epoch 31/100
_loss: 7.4254 - val_mae: 2.2018
Epoch 32/100
_loss: 8.1674 - val_mae: 2.2386
Epoch 33/100
_loss: 8.0326 - val_mae: 2.3014
Epoch 34/100
_loss: 8.4889 - val_mae: 2.2535
Epoch 35/100
loss: 7.8751 - val mae: 2.2566
Epoch 36/100
_loss: 8.8717 - val_mae: 2.3266
Epoch 37/100
_loss: 7.5180 - val_mae: 2.1030
Epoch 38/100
_loss: 8.1002 - val_mae: 2.2648
Epoch 39/100
_loss: 8.8025 - val_mae: 2.2785
Epoch 40/100
_loss: 8.9794 - val_mae: 2.3580
Epoch 41/100
_loss: 9.9753 - val_mae: 2.3709
Epoch 42/100
_loss: 7.9795 - val_mae: 2.0889
Epoch 43/100
_loss: 10.5150 - val_mae: 2.4153
```

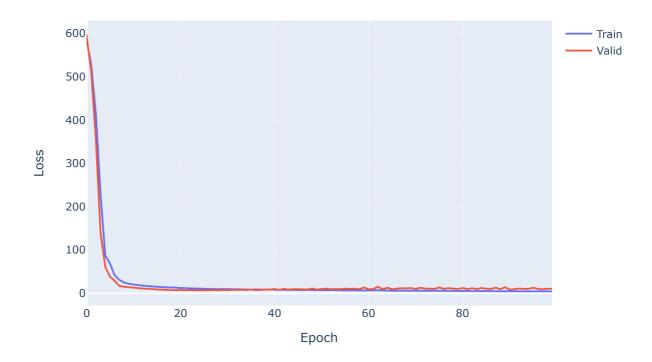
```
Epoch 44/100
_loss: 8.6287 - val_mae: 2.1062
Epoch 45/100
_loss: 9.9041 - val_mae: 2.3241
Epoch 46/100
_loss: 9.5402 - val_mae: 2.3069
Epoch 47/100
_loss: 9.4378 - val_mae: 2.1830
Epoch 48/100
loss: 9.0714 - val mae: 2.1586
Epoch 49/100
loss: 11.2426 - val mae: 2.4920
Epoch 50/100
loss: 8.8415 - val mae: 2.1104
Epoch 51/100
loss: 10.1686 - val mae: 2.2783
Epoch 52/100
loss: 11.0064 - val mae: 2.4006
Epoch 53/100
_loss: 9.8080 - val_mae: 2.2374
Epoch 54/100
_loss: 10.0752 - val_mae: 2.2426
Epoch 55/100
_loss: 9.7234 - val_mae: 2.1608
Epoch 56/100
_loss: 11.0961 - val_mae: 2.2905
Epoch 57/100
loss: 10.4070 - val mae: 2.1456
Epoch 58/100
```

```
_loss: 11.0708 - val_mae: 2.2439
Epoch 59/100
loss: 9.6628 - val mae: 2.1254
Epoch 60/100
_loss: 13.6515 - val_mae: 2.6828
Epoch 61/100
_loss: 9.3899 - val_mae: 2.0708
Epoch 62/100
_loss: 10.2449 - val_mae: 2.1583
Epoch 63/100
_loss: 15.3057 - val_mae: 2.8083
Epoch 64/100
_loss: 9.6575 - val_mae: 2.1116
Epoch 65/100
_loss: 13.0014 - val_mae: 2.5703
Epoch 66/100
_loss: 9.5504 - val_mae: 2.0946
Epoch 67/100
_loss: 10.8695 - val_mae: 2.3231
Epoch 68/100
loss: 11.9418 - val mae: 2.3970
Epoch 69/100
loss: 11.5588 - val mae: 2.3644
Epoch 70/100
loss: 12.2379 - val_mae: 2.4350
Epoch 71/100
_loss: 10.2314 - val_mae: 2.2290
Epoch 72/100
_loss: 12.9785 - val_mae: 2.5009
Epoch 73/100
_loss: 11.0406 - val_mae: 2.3469
Epoch 74/100
_loss: 10.8766 - val_mae: 2.2563
Epoch 75/100
_loss: 10.3696 - val_mae: 2.2330
Epoch 76/100
loss: 13.6397 - val mae: 2.6219
Epoch 77/100
loss: 10.5364 - val mae: 2.2132
Epoch 78/100
_loss: 12.0012 - val_mae: 2.3778
Epoch 79/100
_loss: 10.8913 - val_mae: 2.2944
Epoch 80/100
_loss: 10.1399 - val_mae: 2.2420
```

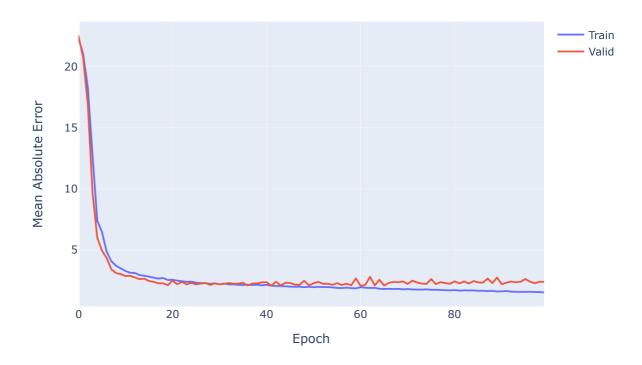
```
Epoch 81/100
_loss: 12.3128 - val_mae: 2.4446
Epoch 82/100
_loss: 9.7143 - val_mae: 2.2702
Epoch 83/100
_loss: 11.8781 - val_mae: 2.4303
Epoch 84/100
_loss: 9.7900 - val_mae: 2.2606
Epoch 85/100
loss: 12.3043 - val mae: 2.4673
Epoch 86/100
loss: 10.8030 - val mae: 2.3560
Epoch 87/100
loss: 10.1529 - val mae: 2.3359
Epoch 88/100
loss: 13.0737 - val mae: 2.6694
Epoch 89/100
loss: 9.7038 - val mae: 2.2990
Epoch 90/100
_loss: 14.3217 - val_mae: 2.7515
Epoch 91/100
_loss: 8.5998 - val_mae: 2.2014
Epoch 92/100
1_loss: 9.7320 - val_mae: 2.3338
Epoch 93/100
_loss: 11.2011 - val_mae: 2.4265
Epoch 94/100
_loss: 10.4882 - val_mae: 2.3658
Epoch 95/100
loss: 10.4736 - val mae: 2.4078
Epoch 96/100
_loss: 12.9197 - val_mae: 2.6341
Epoch 97/100
_loss: 10.3873 - val_mae: 2.4167
Epoch 98/100
_loss: 9.4391 - val_mae: 2.2909
Epoch 99/100
_loss: 10.8212 - val_mae: 2.4048
Epoch 100/100
_loss: 10.5794 - val_mae: 2.3931
```

In []:

```
In [31]: from plotly.subplots import make_subplots
    import plotly.graph_objects as go
    fig = go.Figure()
    fig.add_trace(go.Scattergl(y=history.history['loss'],
        name='Train'))
    fig.add_trace(go.Scattergl(y=history.history['val_loss'],
        name='Valid'))
    fig.update_layout(height=500, width=700,
        xaxis_title='Epoch',
        yaxis_title='Loss')
    fig.show()
```



```
In [32]: fig = go.Figure()
    fig.add_trace(go.Scattergl(y=history.history['mae'],
        name='Train'))
    fig.add_trace(go.Scattergl(y=history.history['val_mae'],
        name='Valid'))
    fig.update_layout(height=500, width=700,
        xaxis_title='Epoch',
        yaxis_title='Mean Absolute Error')
    fig.show()
```



```
In [35]: print('Mean squared error on test data: ', mse lr)
        print('Mean absolute error on test data: ', mae lr)
        from sklearn.metrics import r2 score
        r2 = r2_score(y_test, y_pred)
        print(r2)
        Mean squared error on test data: 28.405854810508238
        Mean absolute error on test data: 3.691362677116256
        0.7944894528123007
In [36]: # Predicting RMSE the Test set results
        from sklearn.metrics import mean_squared_error
        rmse = (np.sqrt(mean squared error(y test, y pred)))
        print(rmse)
        4.075662565490449
In [37]: import sklearn
        new_data = sklearn.preprocessing.StandardScaler().fit_transform(([[0.1, 10.0,
        5.0, 0, 0.4, 6.0, 50, 6.0, 1, 400, 20, 300, 10]]))
        prediction = model.predict(new_data)
        print("Predicted house price:", prediction)
        1/1 [=======] - 0s 193ms/step
        Predicted house price: [[10.683548]]
In [38]: 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)
        Mean squared error on test data: 16.611026763916016
        Mean absolute error on test data: 2.5777082443237305
```

In []: