```
In [1]: import numpy as np
         import pandas as pd
         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
         '1.3.6' or newer of 'bottleneck' (version '1.3.5' currently installed). from pandas.core import (
 In [2]: import keras
          from keras.models import Sequential # To define a sequential model
         from keras.layers import Dense
 In [3]:
         boston = pd.read_csv("boston_house_prices.csv")
 In [4]:
         boston.head()
Out [4]:
              CRIM
                      ΖN
                          INDUS CHAS
                                         NOX
                                                 RM
                                                     AGE
                                                              DIS RAD
                                                                        TAX PTRATIO
                                                                                           B LSTAT
                                                                                                      PRICE
         0.00632
                    18.0
                          2.31
                                  0
                                         0.538
                                               6.575
                                                     65.2
                                                          4.0900
                                                                        296
                                                                             15.3
                                                                                       396.90 4.98
                                                                                                      24.0
                                  0
         1 0.02731 0.0
                          7.07
                                        0.469
                                              6.421 78.9
                                                          4.9671 2
                                                                        242
                                                                             17.8
                                                                                       396.90 9.14
                                                                                                      21.6
                                  0
                                              7.185 61.1 4.9671 2
                                                                                       392.83 4.03
         2 0.02729 0.0
                          7.07
                                        0.469
                                                                        242
                                                                            17.8
                                                                                                      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
 In [6]: boston.columns
dtype='object')
 In [8]:
         boston.shape
Out [8]: (506, 14)
In [10]: boston describe
Out [10]: <bound method NDFrame.describe of
                                              CRIM
                                                      ZN INDUS
                                                                CHAS
                                                                       NOX
                                                                              RM AGE
                                                                                          DIS RAD TAX \
                                                  65.2
78.9
             0.00632 18.0
                          2.31
                                   0 0.538
                                            6.575
                                                        4.0900
                                                                    296
             0.02731
                      0.0
                                   0 0.469
                                            6.421
7.185
                                                       4.9671
                                                                    242
                                                        4.9671
             0.02729
                      0.0
                           7.07
                                   0 0.469
                                                  61.1
                                                                    242
                                      0.458
                                             6.998
                                                   45.8
                                                        6.0622
             0.03237
                                                                 3
             0.06905
                      0.0
                           2.18
                                   0
                                      0.458
                                            7.147
                                                   54.2
                                                        6.0622
                                                                    222
        501
             0.06263
                      0.0
                          11.93
                                   0
                                      0.573
                                            6.593
                                                   69.1
                                                        2
                                                          .4786
                                                                    273
             0.04527
                                   0
                                      0.573
        502
                      0.0
                          11.93
                                            6.120
                                                   76.7
                                                        2.2875
                                                                    273
            0.06076
                                   0 0.573
                                                                    273
                      0.0
                          11.93
                                            6.976
                                                   91.0
                                                        2.1675
        504
             0.10959
                      0.0
                          11.93
                                      0.573
                                            6.794
                                                   89.3
                                                        2.3889
                                                                    273
        505
             0.04741
                      0.0
                          11.93
                                   0 0.573
                                            6.030
                                                   80.8
                                                        2.5050
                     B
396.90
             PTRATIO
                                  PRICE
                           LSTAT
        0
               15.3
                             4.98
                                   24.0
                     396.90
                                   21.6
                17.8
18.7
                     392.83
394.63
                             4.03
2.94
                                   34.7
        3
                                   33.4
                18.7
                    396.90
                             5.33
               21.0
        501
                             9.67
                     391.99
               21.0
                     396.90
                             9.08
                                   20.6
               21.0
21.0
                     396.90
393.45
                             5.64
6.48
                                   23.9
22.0
        503
        504
        505
                21.0
                     396.90
                             7.88
        [506 rows x 14 columns]>
In [11]: boston.info()
         <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 506 entries, 0 to 505 Data columns (total 14 columns):
                     Non-Null Count Dtype
             Column
         0
             CRIM
                     506 non-null
                                    float64
                     506 non-null
             TNDUS
                     506 non-null
                                    float64
             CHAS
                     506 non-null
                                    int64
             NOX
                     506 non-null
                                    float64
         5
             RM
                     506 non-null
                                    float64
                     506 non-null
             AGE
                                    float64
             DIS
                     506 non-null
                                    float64
             RAD
                     506 non-null
                                    int64
                     506 non-null
                                    int64
             TAX
          10
            PTRATIO
                     506 non-null
                                    float64
```

В

506 non-null

float64

```
13 PRICE
                     506 non-null
                                   float64
        dtypes: float64(11), int64(3)
        memory usage: 55.5 KB
In [18]: boston.isnull().sum().sum()
Out [18]: 0
In [20]: | boston.isnull().sum()
Out [20]: CRIM
        INDUS
        CHAS
                  0
        NOX
        RM
        AGE
        RAD
        TAX
        PTRATIO
        LSTAT
        PRICE
        dtype: int64
In [24]: X = boston.iloc[:, :-1]
         y = boston.iloc[:,-1]
In [25]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4)
In [26]: | scaler = StandardScaler() # Initializing StandardScaler
         X_train_scaled = scaler.fit_transform(X_train) # Fit and transform training data
         X_test_scaled = scaler.transform(X_test)
In [27]: lr_model = LinearRegression() # Initializing Linear Regression Model
         lr_model.fit(X_train_scaled, y_train)
Out [27]: LinearRegression
        LinearRegression()
In [28]: y_pred_lr = lr_model.predict(X_test_scaled)
In [29]:
        mse_lr = mean_squared_error(y_test, y_pred_lr) # Mean Squared Error
         mae_lr = mean_absolute_error(y_test, y_pred_lr) # Mean Absolute Error
         r2_1r = r2_score(y_test, y_pred_1r) # R^2 Score (Model accuracy measure)
         # Displaying evaluation metrics
         print("Linear Regression Model Evaluation:")
         print(f"Mean Squared Error: {mse_lr}")
         print(f"Mean Absolute Error: {mae_lr}")
         print(f"R2 Score: {r2_lr}")
        Linear Regression Model Evaluation:
        Mean Squared Error: 25.41958712682183
        Mean Absolute Error: 3.367790983796574
        R2 Score: 0.7263451459702512
In [32]: | model = Sequential([
         Dense(128, activation='relu', input_dim=13), # Input layer (3 features) & first hidden layer (128 neurons)
         Dense(64, activation='relu'), # Second hidden layer with 64 neurons
         Dense(32, activation='relu'), # Third hidden layer with 32 neurons
         Dense(16, activation='relu'), # Fourth hidden layer with 16 neurons
         Dense(1) # Output layer (Predicting a single value - House Price)
         # Compiling the model
         model.compile(optimizer='adam', loss='mse', metrics=['mae'])
         C:\Users\OM\AppData\Roaming\Python\Python311\site-packages\keras\src\layers\core\dense.py:87: 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)
In [33]: history = model.fit(X_train_scaled, y_train, epochs=100, validation_split=0.05, verbose=1)
        Epoch 1/100
        [1m12/12 [Om [32m-
                                                   -[Om[37m[0m [1m22s[0m 207ms/step - loss: 549.5116 - mae: 21.8044 - val_loss: 402.6525 - val_mae: 19.0
        Epoch 2/100
                                                   [1m12/12 [Om [32m
        Epoch 3/100
        .
[1m12/12 [0m [32m-
                                                   _[Om[37m[0m [1m0s[0m 14ms/step - loss: 294.9018 - mae: 14.7023 - val_loss: 100.4361 - val_mae: 9.021
```

12 LSTAT

Epoch 4/100

506 non-null

float64

[1m12/12 [Om	[32m—	[Om [37m [Om	[1m0s [0m	26ms/step	- loss:	110.3882	- mae:	8.2656	- val_loss	: 52.0823	- val_mae	: 6.3884
Epoch 5/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m1s [Om	21ms/step	- loss:	70.3003	- mae: 6	.5354 -	val_loss:	25.1947	- val_mae:	4.2947
Epoch 6/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	19ms/step	- loss:	36.1650	- mae: 4	.3644 -	val_loss:	11.9273	- val_mae:	2.8416
Epoch 7/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	17ms/step	- loss:	24.8440	- mae: 3	.8076 -	val_loss:	7.8919 -	val_mae:	2.2425
Epoch 8/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	22.6092	- mae: 3	.4037 -	val_loss:	6.6428 -	val_mae:	2.1221
Epoch 9/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	24ms/step	- loss:	15.0737	- mae: 2	.8003 -	val_loss:	6.5706 -	val_mae:	2.0850
Epoch 10/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	19ms/step	- loss:	16.3587	- mae: 2	.9302 -	val_loss:	6.4549 -	val_mae:	2.1019
Epoch 11/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	21.3558	- mae: 3	.0639 -	val_loss:	6.4152 -	val_mae:	2.0744
Epoch 12/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	18ms/step	- loss:	15.0428	- mae: 2	.7416 -	val_loss:	6.2342 -	val_mae:	1.9934
Epoch 13/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	13.7386	- mae: 2	.7507 -	val_loss:	6.1867 -	val_mae:	2.0261
Epoch 14/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	17ms/step	- loss:	11.9086	- mae: 2	.5248 -	val_loss:	6.3960 -	val_mae:	1.9694
Epoch 15/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	19ms/step	- loss:	14.4385	- mae: 2	.7014 -	val_loss:	5.8034 -	val_mae:	1.8809
Epoch 16/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	10.7620	- mae: 2	.3470 -	val_loss:	6.0085 -	val_mae:	1.9316
Epoch 17/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	18ms/step	- loss:	16.5408	- mae: 2	.7046 -	val_loss:	6.2809 -	val_mae:	1.9236
Epoch 18/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	20ms/step	- loss:	11.2754	- mae: 2	.3570 -	val_loss:	5.7456 -	val_mae:	1.8806
Epoch 19/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	11.2569	- mae: 2	.4435 -	val_loss:	6.6163 -	val_mae:	1.9459
Epoch 20/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	13ms/step	- loss:	11.9238	- mae: 2	.5025 -	val_loss:	5.5114 -	val_mae:	1.8192
Epoch 21/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	14.4591	- mae: 2	.4678 -	val_loss:	5.7948 -	val_mae:	1.8425
Epoch 22/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	15ms/step	- loss:	9.7901 -	mae: 2.	2451 -	val_loss:	5.7928 - 9	val_mae: 1	.8384
Epoch 23/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	15ms/step	- loss:	9.1815 -	mae: 2.	2736 -	val_loss: 4	4.9069 - 1	val_mae: 1	.7959
Epoch 24/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	18ms/step	- loss:	8.8860 -	mae: 2.	2276 -	val_loss: 0	5.2830 - 9	val_mae: 1	.9156
Epoch 25/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1m1s [Om	14ms/step	- loss:	12.9095	- mae: 2	.3663 -	val_loss:	4.8837 -	val_mae:	1.7791
Epoch 26/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	21ms/step	- loss:	13.3921	- mae: 2	.3648 -	val_loss:	5.5222 -	val_mae:	1.8161
Epoch 27/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1m0s [0m	11ms/step	- loss:	10.4090	- mae: 2	.1994 -	val_loss:	5.2954 -	val_mae:	1.8099
Epoch 28/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	16ms/step	- loss:	10.3735	- mae: 2	.1638 -	val_loss:	4.8744 -	val_mae:	1.7566
Epoch 29/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	17ms/step	- loss:	8.3131 -	mae: 2.	0868 -	val_loss:	5.9593 - 1	val_mae: 1	.8945
Epoch 30/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	7.9329 -	mae: 2.	0326 -	val_loss:	5.3519 - 1	val_mae: 1	.8032
Epoch 31/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	12ms/step	- loss:	9.2763 -	mae: 2.	1416 -	val_loss:	5.2545 - 1	val_mae: 1	.8281
Epoch 32/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	15ms/step	- loss:	8.1264 -	mae: 2.	0106 -	val_loss: 4	4.9861 - 1	val_mae: 1	.7613
Epoch 33/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	12ms/step	- loss:	7.6154 -	mae: 2.	0318 -	val_loss: 4	4.7375 -	val_mae: 1	.7328
Epoch 34/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1m0s [0m	14ms/step	- loss:	12.0724	- mae: 2	.2385 -	val_loss:	4.9443 -	val_mae:	1.7597
Epoch 35/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1m0s [0m	21ms/step	- loss:	7.5880 -	mae: 1.	9634 -	val_loss: 4	4.8182 - 9	val_mae: 1	.7918
Epoch 36/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1m0s [0m	14ms/step	- loss:	7.3464 -	mae: 1.	9208 -	val_loss: 4	4.9693 -	val_mae: 1	.7646
Epoch 37/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	19ms/step	- loss:	6.8558 -	mae: 1.	8410 -	val_loss: 4	4.6264 -	val_mae: 1	.7086
Epoch 38/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1m0s [0m	11ms/step	- loss:	9.1554 -	mae: 2.	0002 -	val_loss: 4	4.8801 - 1	val_mae: 1	.8048
Epoch 39/100 [1m12/12[0m	[32m—	[Om [37m [Om	[1mOs [Om	13ms/step	- loss:	9.5853 -	mae: 2.	0179 -	val_loss:	5.1495 -	val_mae: 1	.7530
Epoch 40/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	11ms/step	- loss:	6.5299 -	mae: 1.	8356 -	val_loss: 5	5.0869 -	val_mae: 1	.7791
Epoch 41/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	7.2939 -	mae: 1.	8407 -	val_loss: 4	4.7951 -	val_mae: 1	.7351
Epoch 42/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	14ms/step	- loss:	8.8814 -	mae: 1.	9153 -	val_loss:	5.2479 -	val_mae: 1	.8361
Epoch 43/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	19ms/step	- loss:	8.9590 -	mae: 2.	0088 -	val_loss: 4	4.9819 -	val_mae: 1	.8302
Epoch 44/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	17ms/step	- loss:	6.6945 -	mae: 1.	8723 -	val_loss: 4	4.3550 -	val_mae: 1	.6864
Epoch 45/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	20ms/step	- loss:	6.3712 -	mae: 1.	8540 -	val_loss: 4	4.2182 -	val_mae: 1	.8049
Epoch 46/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	11ms/step	- loss:	5.5590 -	mae: 1.	7426 -	val_loss:	5.4906 -	val_mae: 1	.8787
Epoch 47/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	11ms/step	- loss:	6.4291 -	mae: 1.	7542 -	val_loss:	5.0850 -	val_mae: 1	.7853
Epoch 48/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1m0s [0m	13ms/step	- loss:	7.7753 -	mae: 1.	9620 -	val_loss: 4	4.2119 -	val_mae: 1	.8052
Epoch 49/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	11ms/step	- loss:	5.9650 -	mae: 1.	7789 -	val_loss: !	5.8454 -	val_mae: 1	.9009
Epoch 50/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	11ms/step	- loss:	5.1682 -	mae: 1.	6709 -	val_loss:	5.2678 -	val_mae: 1	.8551
Epoch 51/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	11ms/step	- loss:	6.4326 -	mae: 1.	8791 -	val_loss: 4	4.6717 -	val_mae: 1	.8802
Epoch 52/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	14ms/step	- loss:	7.5427 -	mae: 1.	9518 -	val_loss: 4	4.4100 -	val_mae: 1	.8116
Epoch 53/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	17ms/step	- loss:	5.6655 -	mae: 1.	7381 -	val_loss: 4	4.5281 -	val_mae: 1	.8300
Epoch 54/100 [1m12/12 [0m	[32m—	[Om [37m [Om	[1mOs [Om	18ms/step	- loss:	6.3646 -	mae: 1.	8299 -	val_loss:	5.4328 -	val_mae: 1	.9223
Epoch 55/100												

```
[1m12/12[Om [32m
                                                  [Om[37m[0m [1m0s[0m 13ms/step - loss: 6.2987 - mae: 1.7489 - val_loss: 5.2997 - val_mae: 1.9369
Epoch 56/100
[1m12/12 [Om [32m
                                                  [Om[37m[0m [1m0s[0m 18ms/step - loss: 4.9288 - mae: 1.5606 - val_loss: 5.6198 - val_mae: 1.9757
Epoch 57/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 16ms/step - loss: 5.8097 - mae: 1.7481 - val_loss: 5.9288 - val_mae: 1.9656
Epoch 58/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1mOs [Om 11ms/step - loss: 5.1237 - mae: 1.6716 - val loss: 5.9587 - val mae: 2.0220
Epoch 59/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 15ms/step - loss: 5.1763 - mae: 1.6840 - val loss: 4.9595 - val mae: 1.9189
Epoch 60/100
[1m12/12 [0m [32m-
                                                  [Om[37m[0m [1m0s[0m 11ms/step - loss: 5.0444 - mae: 1.6479 - val_loss: 5.0309 - val_mae: 1.9479
Epoch 61/100
[1m12/12 [0m [32m-
                                                  [Om[37m[0m [1m0s[0m 12ms/step - loss: 4.8980 - mae: 1.6062 - val_loss: 4.8783 - val_mae: 1.9099
Epoch 62/100
[1m12/12 [Om [32m
                                                  [Om [37m [0m [1m0s [0m 20ms/step - loss: 4.6103 - mae: 1.6085 - val_loss: 4.7392 - val_mae: 1.9074
Epoch 63/100
[1m12/12 [0m [32m
                                                  [Om [37m [0m [1m0s [0m 11ms/step - loss: 4.7150 - mae: 1.5570 - val_loss: 5.2409 - val_mae: 1.9913
Fnoch 64/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1mOs [Om 12ms/step - loss: 4.9795 - mae: 1.5709 - val_loss: 5.4646 - val_mae: 1.9737
Epoch 65/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1m0s [Om 13ms/step - loss: 4.5279 - mae: 1.5737 - val loss: 5.8937 - val mae: 1.9655
Epoch 66/100
.
[1m12/12 [Om [32m-
                                                  [Om [37m [Om [1mOs [Om 15ms/step - loss: 3.9913 - mae: 1.5013 - val loss: 6.7563 - val mae: 2.1813
Epoch 67/100
[1m12/12 [0m [32m-
                                                  [Om [37m [0m [1m0s [0m 11ms/step - loss: 4.4663 - mae: 1.5470 - val_loss: 4.9811 - val_mae: 1.9530
Epoch 68/100
[1m12/12 [0m [32m-
                                                  [Om [37m [0m [1m0s [0m 19ms/step - loss: 4.0378 - mae: 1.4770 - val_loss: 5.4439 - val_mae: 1.9365
Epoch 69/100
[1m12/12 [0m [32m
                                                  [Om[37m[0m [1m0s[0m 17ms/step - loss: 4.3834 - mae: 1.5772 - val_loss: 6.0779 - val_mae: 2.1283
Epoch 70/100
[1m12/12 [Om [32m
                                                  [Om[37m[0m [1m0s[0m 15ms/step - loss: 3.9883 - mae: 1.4828 - val_loss: 5.8573 - val_mae: 2.0260
Epoch 71/100
[1m12/12 [Om [32m
                                                  [Om[37m[Om [1mOs[Om 18ms/step - loss: 3.9218 - mae: 1.4339 - val_loss: 5.9514 - val_mae: 2.0491
Epoch 72/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 17ms/step - loss: 4.1200 - mae: 1.4994 - val_loss: 5.7802 - val_mae: 2.0665
Epoch 73/100
[1m12/12 [Om [32m-
                                                  [Om [37m [Om [1m1s [Om 32ms/step - loss: 3.9186 - mae: 1.3847 - val loss: 5.9706 - val mae: 2.1023
Epoch 74/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1mOs [Om 13ms/step - loss: 3.3908 - mae: 1.3816 - val loss: 6.2767 - val mae: 2.0832
Epoch 75/100
[1m12/12 [0m [32m-
                                                  [Om[37m[0m [1m0s[0m 13ms/step - loss: 3.0234 - mae: 1.2676 - val_loss: 6.0683 - val_mae: 2.1107
Epoch 76/100
[1m12/12 [Om [32m-
                                                  [Om[37m[0m [1m0s[0m 16ms/step - loss: 3.8300 - mae: 1.4123 - val_loss: 5.6242 - val_mae: 2.0047
Epoch 77/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 14ms/step - loss: 3.5744 - mae: 1.3671 - val loss: 5.6237 - val mae: 2.0690
Epoch 78/100
[1m12/12 [0m [32m
                                                  [Om[37m[0m [1m0s[0m 18ms/step - loss: 4.2757 - mae: 1.5079 - val_loss: 5.3630 - val_mae: 1.9960
Epoch 79/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1mOs [Om 14ms/step - loss: 2.9783 - mae: 1.2444 - val loss: 5.8574 - val mae: 2.0549
Epoch 80/100
[1m12/12 [Om [32m
                                                  [Om [37m [Om [1mOs [Om 15ms/step - loss: 2.9691 - mae: 1.3098 - val_loss: 5.8569 - val_mae: 2.0782
Epoch 81/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 15ms/step - loss: 3.1347 - mae: 1.3190 - val loss: 5.6004 - val mae: 2.0516
Epoch 82/100
[1m12/12 [Om [32m-
                                                  [Om[37m[0m [1m0s[0m 21ms/step - loss: 3.0486 - mae: 1.3098 - val_loss: 5.7978 - val_mae: 2.0725
Epoch 83/100
[1m12/12 [0m [32m
                                                  [Om[37m[0m [1m0s[0m 14ms/step - loss: 3.5143 - mae: 1.3388 - val_loss: 6.4607 - val_mae: 2.1463
Epoch 84/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 17ms/step - loss: 3.2677 - mae: 1.3296 - val loss: 7.1982 - val mae: 2.2619
Epoch 85/100
[1m12/12 [Om [32m
                                                  [Om [37m [0m [1m0s [0m 14ms/step - loss: 2.7845 - mae: 1.2696 - val_loss: 6.3011 - val_mae: 2.1320
Epoch 86/100
[1m12/12 [Om [32m
                                                  [Om[37m[0m [1m0s[0m 14ms/step - loss: 3.2645 - mae: 1.3261 - val_loss: 5.9456 - val_mae: 2.0780
Epoch 87/100
[1m12/12 [Om [32m
                                                  [Om [37m [Om [1mOs [Om 14ms/step - loss: 3.3792 - mae: 1.3207 - val_loss: 6.5349 - val_mae: 2.1487
Epoch 88/100
[1m12/12 [Om [32m-
                                                  [Om [37m [Om [1mOs [Om 14ms/step - loss: 3.0326 - mae: 1.3049 - val loss: 7.2766 - val mae: 2.3267
Epoch 89/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1mOs [Om 17ms/step - loss: 2.7410 - mae: 1.2498 - val loss: 6.5947 - val mae: 2.1601
Epoch 90/100
[1m12/12 [0m [32m-
                                                  [Om [37m [Om [1mOs [Om 12ms/step - loss: 2.6835 - mae: 1.2105 - val_loss: 7.8742 - val_mae: 2.3418
Epoch 91/100
[1m12/12[0m [32m-
                                                  [Om[37m[0m [1m0s[0m 17ms/step - loss: 2.8822 - mae: 1.2184 - val_loss: 6.2158 - val_mae: 2.1801
Epoch 92/100
[1m12/12 [0m [32m
                                                  [Om[37m[0m [1m0s[0m 13ms/step - loss: 2.8245 - mae: 1.2308 - val_loss: 5.7484 - val_mae: 2.0469
Epoch 93/100
[1m12/12 [0m [32m-
                                                  [Om[37m[0m [1m0s[0m 14ms/step - loss: 3.0690 - mae: 1.2606 - val_loss: 5.7192 - val_mae: 2.0031
Epoch 94/100
[1m12/12 [0m [32m-
                                                  [Om[37m[0m [1m0s[0m 12ms/step - loss: 2.4758 - mae: 1.1528 - val_loss: 5.7537 - val_mae: 2.0362
Epoch 95/100
[1m12/12 [Om [32m
                                                  [Om[37m[0m [1m0s[0m 14ms/step - loss: 2.8690 - mae: 1.2372 - val_loss: 6.3387 - val_mae: 2.1342
Epoch 96/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 16ms/step - loss: 2.4567 - mae: 1.1880 - val_loss: 5.9458 - val_mae: 2.1252
Epoch 97/100
[1m12/12 [Om [32m-
                                                  [Om [37m [Om [1mOs [Om 15ms/step - loss: 3.1337 - mae: 1.2829 - val loss: 6.4779 - val mae: 2.1510
Epoch 98/100
[1m12/12 [0m [32m
                                                  [Om [37m [Om [1mOs [Om 17ms/step - loss: 2.2902 - mae: 1.1209 - val loss: 6.4647 - val mae: 2.1840
Epoch 99/100
[1m12/12 [Om [32m
                                                  [Om [37m [0m [1m0s [0m 13ms/step - loss: 2.4584 - mae: 1.1437 - val_loss: 6.4062 - val_mae: 2.1606
Epoch 100/100
[1m12/12 [Om [32m-
                                                 [0m[37m[0m [1m0s[0m 15ms/step - loss: 3.1502 - mae: 1.2778 - val_loss: 6.1874 - val_mae: 2.1853 -
```

In [34]: y_pred_nn = model.predict(X_test_scaled) # Predicting house prices on test data
 mse_nn, mae_nn = model.evaluate(X_test_scaled, y_test) # Evaluating model performance
Displaying Neural Network Evaluation Metrics
print("\nNeural Network Model Evaluation:")
print(f"Mean Squared Error: {mse_nn}")
print(f"Mean Absolute Error: {mae_nn}")

```
[1m4/4[0m [32m
                                                               -[Om[37m[Om [1m1s[Om 145ms/step
                                                               -[Om[37m[Om [1mOs[Om 8ms/step - loss: 10.9387 - mae: 2.3844
          [1m4/4 [0m [32m
          Neural Network Model Evaluation:
Mean Squared Error: 9.77536678314209
          Mean Absolute Error: 2.2946557998657227
In [35]: new_data = np.array([[0.1, 10.0, 5.0]])
           # New input values: LSTAT=0.1, RM=10.0, PTRATIO=5.0
           new_data_scaled = scaler.transform(new_data)
           # Applying the same standardization as training data
           # Predicting price using trained neural network model
           prediction = model.predict(new_data_scaled)
           C:\ProgramData\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X does not have valid feature names, but StandardScaler
           was fitted with feature names
            warnings.warn(
                                                                                                                                                Traceback (most recent call last)
                1 new_data = np.array([[0.1, 10.0, 5.0]])
2 # New input values: LSTAT=0.1, RM=10.0, PTRATIO=5.0
          2 # New Input Values: LSIAI=U.1, km=10.0, PIRAI10=5.0
3 new_data_scaled = scaler.transform(new_data)
4 # Applying the same standardization as training data
5 # Predicting price using trained neural network model
6 prediction = model.predict(new_data_scaled)
          File C:\ProgramData\anaconda3\Lib\site-packages\sklearn\utils\_set_output.py:140, in _wrap_method_output.<locals>.wrapped(self, X, *args, **kwargs)
138 @wraps(f)
              --> 140
                            return (
              143
                                 _wrap_data_with_container(method, data_to_wrap[0], X, self), *data_to_wrap[1:],
              145
              146
          File C:\ProgramData\anaconda3\Lib\site-packages\sklearn\preprocessing\_data.py:992, in StandardScaler.transform(self, X, copy)
              989 check_is_fitted(self)
991 copy = copy if copy is not None else self.copy
992 X = self._validate_data(
                       Χ,
              993
              994
                       reset=False,
              995
                       accept_sparse="csr",
                       copy=copy,
dtype=FLOAT_DTYPES,
              996
              997
              998
                       force_all_finite="allow-nan",
              999 )
             1001 if sparse.issparse(X):
             1002
                       if self.with_mean
          File C:\ProgramData\anaconda3\Lib\site-packages\sklearn\base.py:588, in BaseEstimator._validate_data(self, X, y, reset, validate_separately, **check_p
              585 out = X, y
587 if not no_val_X and check_params.get("ensure_2d", True):
                       self._check_n_features(X, reset=reset)
          --> 588
              590 return out
          File C:\ProgramData\anaconda3\Lib\site-packages\sklearn\base.py:389, in BaseEstimator._check_n_features(self, X, reset)
              386
                       return
              388 if n_features != self.n_features_in_:
                       raise ValueError(
    f"X has {n_features} features, but {self.__class__.__name__} "
    f"is expecting {self.n_features_in_} features as input."
          --> 389
              390
              391
              392
          ValueError: X has 3 features, but StandardScaler is expecting 13 features as input.
In [ ]: | # Displaying the predicted house price
           print("\nPredicted House Price:", prediction[0][0])
In [ 1:
```