```
import numpy as np
import pandas as pd

data = pd.read_csv("boston.csv")

data.head()
```

```
   Unnamed: 0     CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS
RAD  \
0           0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900
1.0
1           1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671
2.0
2           2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671
2.0
3           3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622
3.0
4           4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622
3.0

     TAX  PTRATIO       B  LSTAT  Price
0  296.0     15.3  396.90   4.98   24.0
1  242.0     17.8  396.90   9.14   21.6
2  242.0     17.8  392.83   4.03   34.7
3  222.0     18.7  394.63   2.94   33.4
4  222.0     18.7  396.90   5.33   36.2
```

```
data.columns
```

```
Index(['Unnamed: 0', 'CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM',
'AGE', 'DIS',
       'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'Price'],
      dtype='object')
```

```
data.head(n=10)
```

```
   Unnamed: 0     CRIM    ZN  INDUS  CHAS    NOX     RM    AGE     DIS
RAD  \
0           0  0.00632  18.0   2.31   0.0  0.538  6.575   65.2  4.0900
1.0
1           1  0.02731   0.0   7.07   0.0  0.469  6.421   78.9  4.9671
2.0
2           2  0.02729   0.0   7.07   0.0  0.469  7.185   61.1  4.9671
2.0
3           3  0.03237   0.0   2.18   0.0  0.458  6.998   45.8  6.0622
3.0
4           4  0.06905   0.0   2.18   0.0  0.458  7.147   54.2  6.0622
3.0
5           5  0.02985   0.0   2.18   0.0  0.458  6.430   58.7  6.0622
3.0
6           6  0.08829  12.5   7.87   0.0  0.524  6.012   66.6  5.5605
```

```
5.0
7           7  0.14455  12.5   7.87   0.0  0.524  6.172   96.1  5.9505
5.0
8           8  0.21124  12.5   7.87   0.0  0.524  5.631  100.0  6.0821
5.0
9           9  0.17004  12.5   7.87   0.0  0.524  6.004   85.9  6.5921
5.0
```

```
     TAX  PTRATIO       B  LSTAT  Price
0  296.0     15.3  396.90   4.98   24.0
1  242.0     17.8  396.90   9.14   21.6
2  242.0     17.8  392.83   4.03   34.7
3  222.0     18.7  394.63   2.94   33.4
4  222.0     18.7  396.90   5.33   36.2
5  222.0     18.7  394.12   5.21   28.7
6  311.0     15.2  395.60  12.43   22.9
7  311.0     15.2  396.90  19.15   27.1
8  311.0     15.2  386.63  29.93   16.5
9  311.0     15.2  386.71  17.10   18.9
```

```
data.shape
```

```
(506, 15)
```

```
data.isnull().sum()
```

```
Unnamed: 0    0
CRIM          0
ZN            0
INDUS         0
CHAS          0
NOX           0
RM            0
AGE           0
DIS           0
RAD           0
TAX           0
PTRATIO       0
B             0
LSTAT         0
Price         0
dtype: int64
```

```
data.describe()
```

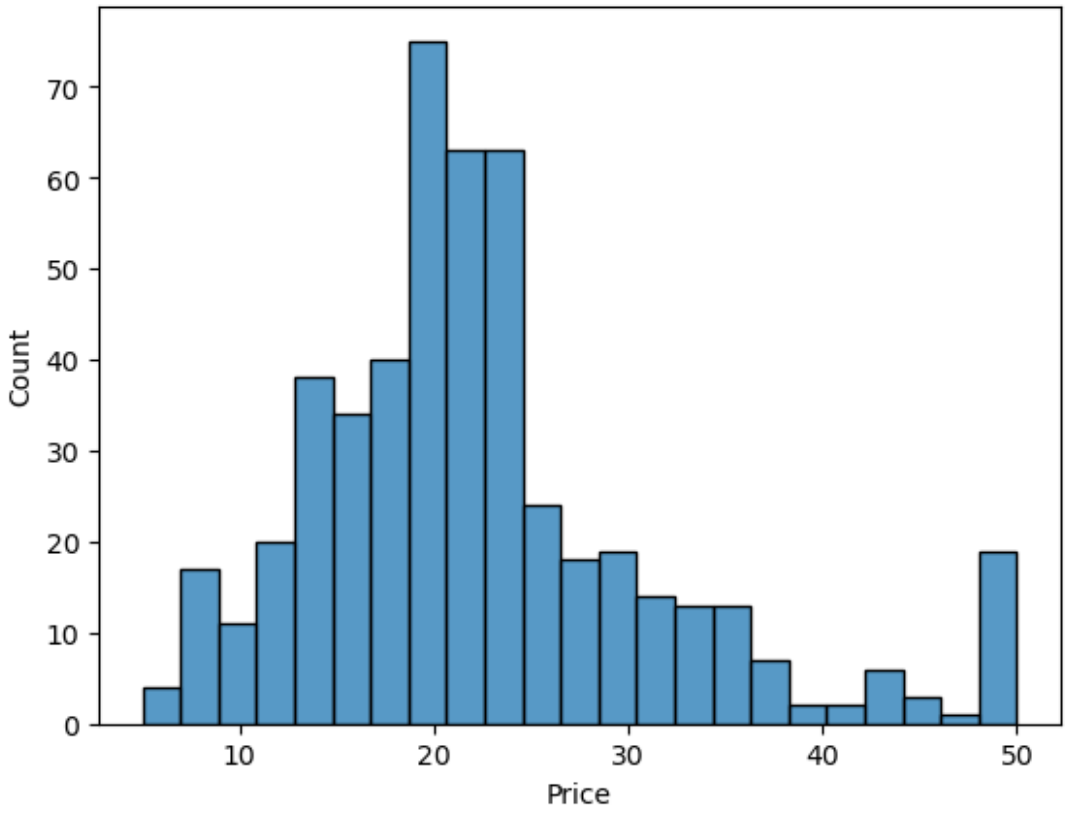
```
       Unnamed: 0        CRIM          ZN       INDUS        CHAS
NOX  \
count  506.000000  506.000000  506.000000  506.000000  506.000000
506.000000
mean   252.500000    3.613524   11.363636   11.136779    0.069170
0.554695
```

```
std    146.213884    8.601545   23.322453    6.860353    0.253994
0.115878
min      0.000000    0.006320    0.000000    0.460000    0.000000
0.385000
25%    126.250000    0.082045    0.000000    5.190000    0.000000
0.449000
50%    252.500000    0.256510    0.000000    9.690000    0.000000
0.538000
75%    378.750000    3.677083   12.500000   18.100000    0.000000
0.624000
max    505.000000   88.976200  100.000000   27.740000    1.000000
0.871000

                RM          AGE          DIS          RAD          TAX
PTRATIO  \
count  506.000000  506.000000  506.000000  506.000000  506.000000
506.000000
mean     6.284634   68.574901    3.795043    9.549407  408.237154
18.455534
std      0.702617   28.148861    2.105710    8.707259  168.537116
2.164946
min      3.561000    2.900000    1.129600    1.000000  187.000000
12.600000
25%      5.885500   45.025000    2.100175    4.000000  279.000000
17.400000
50%      6.208500   77.500000    3.207450    5.000000  330.000000
19.050000
75%      6.623500   94.075000    5.188425   24.000000  666.000000
20.200000
max      8.780000  100.000000   12.126500   24.000000  711.000000
22.000000

                B       LSTAT       Price
count  506.000000  506.000000  506.000000
mean   356.674032   12.653063   22.532806
std     91.294864    7.141062    9.197104
min      0.320000    1.730000    5.000000
25%    375.377500    6.950000   17.025000
50%    391.440000   11.360000   21.200000
75%    396.225000   16.955000   25.000000
max    396.900000   37.970000   50.000000

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 15 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  506 non-null    int64
```

```
 1   CRIM         506 non-null    float64
 2   ZN           506 non-null    float64
 3   INDUS        506 non-null    float64
 4   CHAS         506 non-null    float64
 5   NOX          506 non-null    float64
 6   RM           506 non-null    float64
 7   AGE          506 non-null    float64
 8   DIS          506 non-null    float64
 9   RAD          506 non-null    float64
 10  TAX          506 non-null    float64
 11  PTRATIO      506 non-null    float64
 12  B            506 non-null    float64
 13  LSTAT        506 non-null    float64
 14  Price        506 non-null    float64
dtypes: float64(14), int64(1)
memory usage: 59.4 KB
```

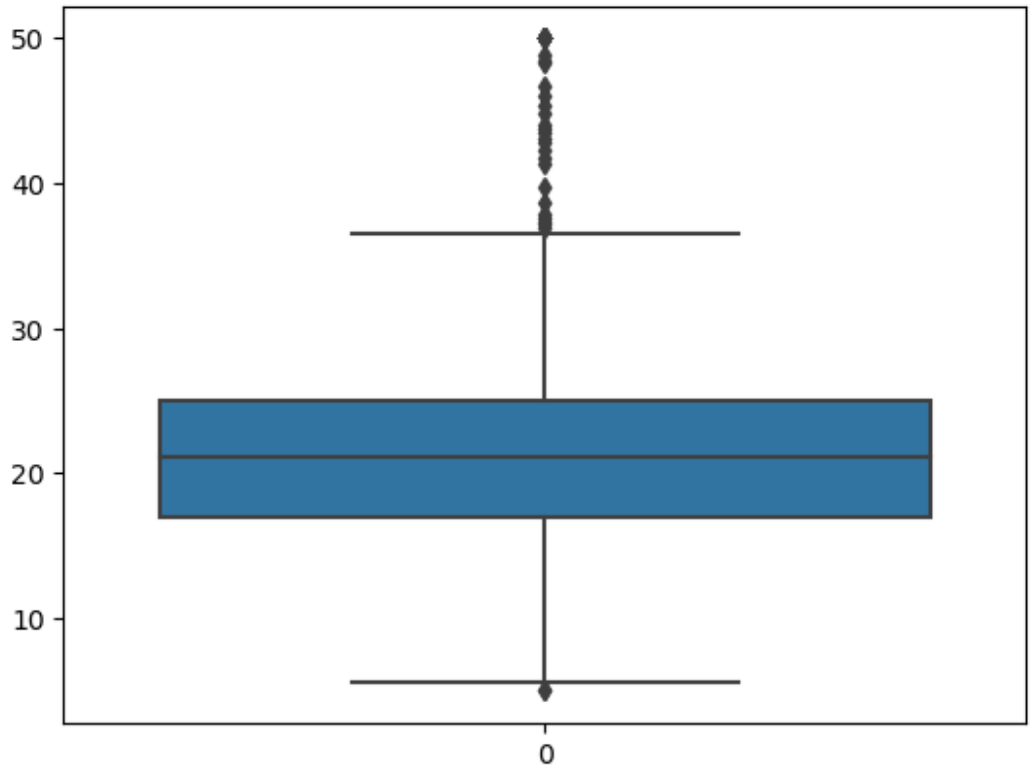
```
import seaborn as sns

sns.histplot(data["Price"])
```

```
<Axes: xlabel='Price', ylabel='Count'>
```




```
sns.boxplot(data["Price"])
```

```
<Axes: >
```




```
from sklearn.preprocessing import StandardScaler
# Split the data into input and output variables
X = data.drop('Price', axis=1)
y =data['Price']
# Scale the input features
scaler =StandardScaler()
X =scaler.fit_transform(X)

from sklearn.model_selection import train_test_split
# Splitthe data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

print('Training set shape:', X_train.shape, y_train.shape)
print('Testing set shape:', X_test.shape, y_test.shape)
```

```
Training set shape: (354, 14) (354,)
Testing set shape: (152, 14) (152,)
```

```
from keras.models import Sequential
from keras.layers import Dense, Dropout

# Define the model architecture
model = Sequential()
```

```
model.add(Dense(128,activation = 'relu',input_dim =14))
model.add(Dense(64,activation = 'relu'))
model.add(Dense(32,activation = 'relu'))
model.add(Dense(16,activation = 'relu'))
model.add(Dense(1))
```

```
C:\Users\STES\anaconda3\Lib\site-packages\keras\src\layers\core\
dense.py:88: 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)
```

```
# Display the model summary
print(model.summary())
```

```
Model: "sequential"
```

```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃ Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ dense (Dense)                        │ (None, 128)                 │ 1,920 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense_1 (Dense)                      │ (None, 64)                  │ 8,256 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense_2 (Dense)                      │ (None, 32)                  │ 2,080 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense_3 (Dense)                      │ (None, 16)                  │ 528 │
├──────────────────────────────────────┼─────────────────────────────┼─────────────────┤
│ dense_4 (Dense)                      │ (None, 1)                   │ 17 │
└──────────────────────────────────────┴─────────────────────────────┴─────────────────┘
```

```
 Total params: 12,801 (50.00 KB)

 Trainable params: 12,801 (50.00 KB)

 Non-trainable params: 0 (0.00 B)
```

```
None
```

```
# Compile the model
model.compile(optimizer = 'adam',loss
='mean_squared_error',metrics=['mae'])

x_val=X_train
y_val=y_train

history = model.fit(X_train,
                    y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val, y_val))
```

```
Epoch 1/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - loss: 624.6559 - mae: 23.1586 -
val_loss: 622.1426 - val_mae: 23.1068
Epoch 2/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 622.1426 - mae: 23.1068
- val_loss: 620.0562 - val_mae: 23.0625
Epoch 3/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 620.0562 - mae: 23.0625
- val_loss: 618.4172 - val_mae: 23.0253
Epoch 4/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 618.4172 - mae: 23.0253
- val_loss: 617.0788 - val_mae: 22.9923
Epoch 5/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 617.0788 - mae: 22.9923
- val_loss: 615.6612 - val_mae: 22.9577
Epoch 6/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 615.6611 - mae: 22.9577
- val_loss: 614.0786 - val_mae: 22.9198
Epoch 7/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 614.0786 - mae: 22.9198
- val_loss: 612.3089 - val_mae: 22.8784
Epoch 8/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 612.3089 - mae: 22.8784
- val_loss: 610.3096 - val_mae: 22.8320
Epoch 9/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 610.3096 - mae: 22.8320
- val_loss: 608.0159 - val_mae: 22.7791
Epoch 10/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 608.0159 - mae: 22.7791
- val_loss: 605.3791 - val_mae: 22.7185
Epoch 11/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 49ms/step - loss: 605.3790 - mae: 22.7185
- val_loss: 602.3395 - val_mae: 22.6489
Epoch 12/20
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 602.3395 - mae: 22.6489
- val_loss: 598.8791 - val_mae: 22.5700
Epoch 13/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 598.8791 - mae: 22.5700
- val_loss: 595.0938 - val_mae: 22.4838
Epoch 14/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 595.0938 - mae: 22.4838
- val_loss: 591.0748 - val_mae: 22.3923
Epoch 15/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 591.0748 - mae: 22.3923
- val_loss: 586.8221 - val_mae: 22.2952
Epoch 16/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 586.8221 - mae: 22.2952
- val_loss: 582.3458 - val_mae: 22.1927
Epoch 17/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 582.3458 - mae: 22.1927
- val_loss: 577.6431 - val_mae: 22.0842
Epoch 18/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 577.6431 - mae: 22.0842
- val_loss: 572.6659 - val_mae: 21.9685
Epoch 19/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 572.6659 - mae: 21.9685
- val_loss: 567.3625 - val_mae: 21.8447
Epoch 20/20
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step - loss: 567.3625 - mae: 21.8447
- val_loss: 561.7023 - val_mae: 21.7116

results = model.evaluate(X_test, y_test)

5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 471.2321 - mae: 20.0160
```