In [2]:

```
# Importing the Dependencies

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.datasets
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn import metrics
```

In [ ]:

```
# Importing the Boston House Price Dataset

house_price_dataset = sklearn.datasets.load_boston()
```

In [7]:

```
print(house_price_dataset)
```

```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+02,
         4.9800e+00],
        [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
         4.0300e+00],
        ...,
        [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         5.6400e+00],
        [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
         6.4800e+00],
        [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         7.8800e+00]]), 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 1
6.5, 18.9, 15. ,
       18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
       15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
       13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
       21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
       35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
       19.4, 22. , 17.4, 20.9, 24.2, 21.7, 22.8, 23.4, 24.1, 21.4, 20. ,
       20.8, 21.2, 20.3, 28. , 23.9, 24.8, 22.9, 23.9, 26.6, 22.5, 22.2,
       23.6, 28.7, 22.6, 22. , 22.9, 25. , 20.6, 28.4, 21.4, 38.7, 43.8,
       33.2, 27.5, 26.5, 18.6, 19.3, 20.1, 19.5, 19.5, 20.4, 19.8, 19.4,
       21.7, 22.8, 18.8, 18.7, 18.5, 18.3, 21.2, 19.2, 20.4, 19.3, 22. ,
       20.3, 20.5, 17.3, 18.8, 21.4, 15.7, 16.2, 18. , 14.3, 19.2, 19.6,
       23. , 18.4, 15.6, 18.1, 17.4, 17.1, 13.3, 17.8, 14. , 14.4, 13.4,
       15.6, 11.8, 13.8, 15.6, 14.6, 17.8, 15.4, 21.5, 19.6, 15.3, 19.4,
       17. , 15.6, 13.1, 41.3, 24.3, 23.3, 27. , 50. , 50. , 50. , 22.7,
       25. , 50. , 23.8, 23.8, 22.3, 17.4, 19.1, 23.1, 23.6, 22.6, 29.4,
       23.2, 24.6, 29.9, 37.2, 39.8, 36.2, 37.9, 32.5, 26.4, 29.6, 50. ,
       32. , 29.8, 34.9, 37. , 30.5, 36.4, 31.1, 29.1, 50. , 33.3, 30.3,
       34.6, 34.9, 32.9, 24.1, 42.3, 48.5, 50. , 22.6, 24.4, 22.5, 24.4,
       20. , 21.7, 19.3, 22.4, 28.1, 23.7, 25. , 23.3, 28.7, 21.5, 23. ,
       26.7, 21.7, 27.5, 30.1, 44.8, 50. , 37.6, 31.6, 46.7, 31.5, 24.3,
       31.7, 41.7, 48.3, 29. , 24. , 25.1, 31.5, 23.7, 23.3, 22. , 20.1,
       22.2, 23.7, 17.6, 18.5, 24.3, 20.5, 24.5, 26.2, 24.4, 24.8, 29.6,
       42.8, 21.9, 20.9, 44. , 50. , 36. , 30.1, 33.8, 43.1, 48.8, 31. ,
       36.5, 22.8, 30.7, 50. , 43.5, 20.7, 21.1, 25.2, 24.4, 35.2, 32.4,
       32. , 33.2, 33.1, 29.1, 35.1, 45.4, 35.4, 46. , 50. , 32.2, 22. ,
       20.1, 23.2, 22.3, 24.8, 28.5, 37.3, 27.9, 23.9, 21.7, 28.6, 27.1,
       20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
       22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
       21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
       19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
       32.7, 16.5, 23.9, 31.2, 17.5, 17.2, 23.1, 24.5, 26.6, 22.9, 24.1,
       18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
```

```
       16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
       13.8, 15. , 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3,  8.8,
        7.2, 10.5,  7.4, 10.2, 11.5, 15.1, 23.2,  9.7, 13.8, 12.7, 13.1,
       12.5,  8.5,  5. ,  6.3,  5.6,  7.2, 12.1,  8.3,  8.5,  5. , 11.9,
       27.9, 17.2, 27.5, 15. , 17.2, 17.9, 16.3,  7. ,  7.2,  7.5, 10.4,
        8.8,  8.4, 16.7, 14.2, 20.8, 13.4, 11.7,  8.3, 10.2, 10.9, 11. ,
        9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4,  9.6,  8.7,  8.4, 12.8,
       10.5, 17.1, 18.4, 15.4, 10.8, 11.8, 14.9, 12.6, 14.1, 13. , 13.4,
       15.2, 16.1, 17.8, 14.9, 14.1, 12.7, 13.5, 14.9, 20. , 16.4, 17.7,
       19.5, 20.2, 21.4, 19.9, 19. , 19.1, 19.1, 20.1, 19.9, 19.6, 23.2,
       29.8, 13.8, 13.3, 16.7, 12. , 14.6, 21.4, 23. , 23.7, 25. , 21.8,
       20.6, 21.2, 19.1, 20.6, 15.2,  7. ,  8.1, 13.6, 20.1, 21.8, 24.5,
       23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.9]), 'feature_names
': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'), 'DESCR': ".. _boston_dataset:\n\nBo
ston house prices dataset\n---------------------------\n\n**Data Set Characteristics:**
\n\n    :Number of Instances: 506 \n\n    :Number of Attributes: 13 numeric/categorical p
redictive. Median Value (attribute 14) is usually the target.\n\n    :Attribute Informati
on (in order):\n        - CRIM     per capita crime rate by town\n        - ZN       pro
portion of residential land zoned for lots over 25,000 sq.ft.\n        - INDUS    proport
ion of non-retail business acres per town\n        - CHAS     Charles River dummy variabl
e (= 1 if tract bounds river; 0 otherwise)\n        - NOX      nitric oxides concentratio
n (parts per 10 million)\n        - RM       average number of rooms per dwelling\n
- AGE      proportion of owner-occupied units built prior to 1940\n        - DIS      wei
ghted distances to five Boston employment centres\n        - RAD      index of accessibil
ity to radial highways\n        - TAX      full-value property-tax rate per $10,000\n
- PTRATIO  pupil-teacher ratio by town\n        - B        1000(Bk - 0.63)^2 where Bk is
the proportion of black people by town\n        - LSTAT    % lower status of the populati
on\n        - MEDV     Median value of owner-occupied homes in $1000's\n\n    :Missing At
tribute Values: None\n\n    :Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy
of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/ml/machine-learning-databases/hou
sing/\n\n\nThis dataset was taken from the StatLib library which is maintained at Carnegi
e Mellon University.\n\nThe Boston house-price data of Harrison, D. and Rubinfeld, D.L. '
Hedonic\nprices and the demand for clean air', J. Environ. Economics & Management,\nvol.5
, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wiley, 19
80.   N.B. Various transformations are used in the table on\npages 244-261 of the latter.
\n\nThe Boston house-price data has been used in many machine learning papers that addres
s regression\nproblems.   \n     \n.. topic:: References\n\n   - Belsley, Kuh & Welsch, '
Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley,
1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning
. In Proceedings on the Tenth International Conference of Machine Learning, 236-243, Univ
ersity of Massachusetts, Amherst. Morgan Kaufmann.\n", 'filename': 'boston_house_prices.c
sv', 'data_module': 'sklearn.datasets.data'}
```


In [9]:

```
# Loading the dataset to a Pandas DataFrame
house_price_dataframe = pd.DataFrame(house_price_dataset.data, columns = house_price_dat
aset.feature_names)
```

In [12]:

```
# Print First 5 rows of our DataFrame
house_price_dataframe.head()
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [14]:

```
# add the target (price) column to the DataFrame
```

```
house_price_dataframe['price'] = house_price_dataset.target
```

In [15]:

```
house_price_dataframe.head()
```

Out[15]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	price
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

In [16]:

```
# checking the number of rows and Columns in the data frame
house_price_dataframe.shape
```

Out[16]:

```
(506, 14)
```

In [17]:

```
# check for missing values
house_price_dataframe.isnull().sum()
```

Out[17]:

```
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
```

In [18]:

```
# statistical measures of the dataset
house_price_dataframe.describe()
```

Out[18]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TA
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.0000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.2371
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.5371
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.0000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.0000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.0000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.0000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.0000

Understanding the correlation between various features in the dataset

1.Positive Correlation

2.Negative Correlation

In [20]:

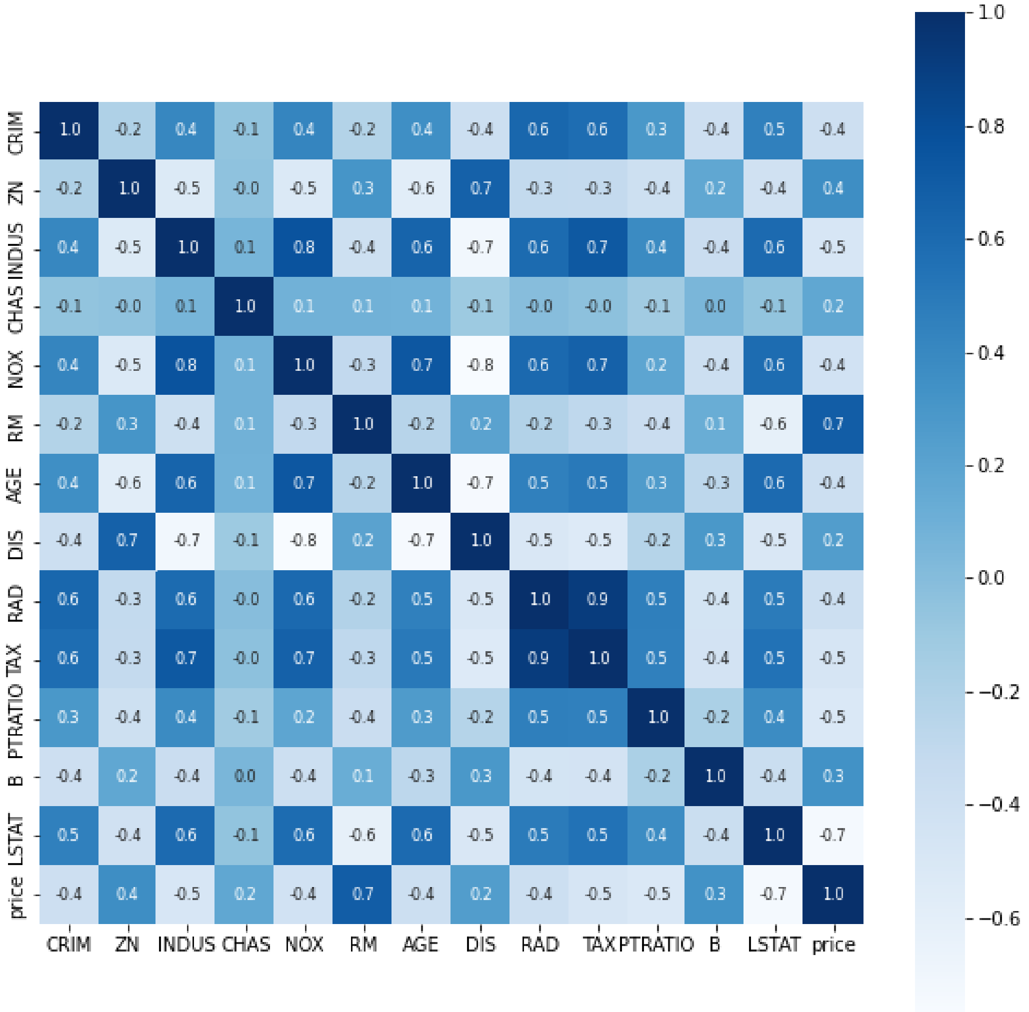
```
correlation = house_price_dataframe.corr()
```

In [21]:

```
# constructing a heatmap to understand the correlation
plt.figure(figsize=(10,10))
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f', annot=True, annot_kws={'size
':8}, cmap='Blues')
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f169ed17dd0>
```



In [22]:

```
# Splitting the data and Target
X = house_price_dataframe.drop(['price'], axis=1)
Y = house_price_dataframe['price']
```

In [23]:

```
print(X)
print(Y)
```

```
         CRIM    ZN  INDUS  CHAS    NOX  ...  RAD    TAX  PTRATIO       B  LSTAT
0     0.00632  18.0   2.31   0.0  0.538  ...  1.0  296.0     15.3  396.90   4.98
1     0.02731   0.0   7.07   0.0  0.469  ...  2.0  242.0     17.8  396.90   9.14
```

```
2    0.02729  0.0   7.07  0.0  0.469  ...  2.0  242.0     17.8  392.83   4.03
3    0.03237  0.0   2.18  0.0  0.458  ...  3.0  222.0     18.7  394.63   2.94
4    0.06905  0.0   2.18  0.0  0.458  ...  3.0  222.0     18.7  396.90   5.33
..       ...  ...    ...  ...    ...  ...  ...    ...      ...     ...    ...
501  0.06263  0.0  11.93  0.0  0.573  ...  1.0  273.0     21.0  391.99   9.67
502  0.04527  0.0  11.93  0.0  0.573  ...  1.0  273.0     21.0  396.90   9.08
503  0.06076  0.0  11.93  0.0  0.573  ...  1.0  273.0     21.0  396.90   5.64
504  0.10959  0.0  11.93  0.0  0.573  ...  1.0  273.0     21.0  393.45   6.48
505  0.04741  0.0  11.93  0.0  0.573  ...  1.0  273.0     21.0  396.90   7.88

[506 rows x 13 columns]
0      24.0
1      21.6
2      34.7
3      33.4
4      36.2
       ...
501    22.4
502    20.6
503    23.9
504    22.0
505    11.9
Name: price, Length: 506, dtype: float64
```

Splitting the data into Training data and Test data

In [24]:

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state
= 2)
```

In [25]:

```
print(X.shape, X_train.shape, X_test.shape)
```

```
(506, 13) (404, 13) (102, 13)
```

In [26]:

```
# Model Training
 # XGBoost Regressor

 # loading the model
model = XGBRegressor()
```

In [ ]:

```
# training the model with X_train
model.fit(X_train, Y_train)
```

In [28]:

```
# Evaluation
# Prediction on training data

# accuracy for prediction on training data
training_data_prediction = model.predict(X_train)
```

In [29]:

```
print(training_data_prediction)
```

```
[23.360205  22.462858  20.84804   33.77895   15.333282  13.616525
 21.71274   15.175322  11.724756  21.836252  16.08508    7.52517
 31.094206  48.56228   32.623158  20.546066  22.177324  20.500404
 31.666502  20.551508  25.74269    8.247894  45.200817  22.069397
 20.698004  20.100042  19.873472  26.242834  23.39618   31.927258
 21.493471   9.280926  18.504272  21.87202   12.504413  10.578829
 13.054951  23.541336  19.164755  15.888303  23.768887  28.454714
 15.539753  18.049202  16.23671   14.08383   25.33273   17.575668
 49.566467  16.990675  21.738977  32.935143  16.125738  22.45393
```

```
 20.776966  20.042227  22.898897  38.124043  30.607079  32.607468
 20.919416  47.348038  14.524615   8.126455  19.581661   9.030508
 26.462107  17.69918   20.546162  46.312218  39.689137  34.387108
 22.11083   34.568977  24.873934  50.078335  14.5669775 20.525211
 20.62971   23.202105  49.514477  23.12061   24.795782  20.319666
 43.869396  17.110266  32.165016  34.75202    7.313497  20.309446
 18.038298  12.008462  24.216425  47.90671   37.94349   20.759708
 40.182804  18.249052  15.611586  26.39461   21.0571    20.421682
 18.377089  17.338768  21.223648  22.653662  17.560051  32.635715
 16.683764  13.004857  18.488163  20.659714  16.501846  20.648884
 48.62411   15.977999  15.97522   18.581459  14.893438  32.871964
 14.236945  43.612328  33.881115  19.073408  15.747335   9.4903965
 10.153891  14.812717  18.655546   8.596755  22.666656  10.941623
 20.534616  49.324417  22.710459  19.99658   31.663935  21.78586
 30.9277    30.507492  15.054665  15.854853  48.532074  21.108742
 15.687305  12.403721  49.90245   31.557863  11.709707  20.22495
 26.214525  32.90807   22.90362    9.542897  24.487959  24.46598
 22.509142  14.704502  27.895067  33.619015  14.888735  19.147383
 26.40218   32.77208   29.293688  23.638102  10.448805  22.518728
 21.47825   35.32415   23.002241  20.470022  18.918747  10.328174
 22.244467  17.69918   20.918488  11.913417  42.572548  46.803394
 14.652036  20.633188  23.285368  15.295161  20.861048  23.587011
 32.94382   21.090906  24.898489  18.465925  31.454802  14.421506
 15.421497  21.890705  23.64799   17.40471   26.111868  24.977922
 27.56308   22.964123  18.823803  28.856464  14.080684  19.785515
 17.007908  42.90537   26.354216  21.719929  23.784258  18.4141
 17.923422  20.337881  22.936398  25.297531  17.572325  14.486319
 20.739832  21.733093  11.1917715 18.290442  20.70475   20.929468
 18.990923   8.7798395 21.141748  21.021317  15.49217   24.455221
 31.499088  22.668139  14.862843  19.69585   24.746317  22.913176
 48.144817  19.950285  30.148172  49.98047   16.743952  16.218952
  9.891141  20.452726  17.06055   14.73646   17.539606  19.555712
 30.26191   27.037518  18.43813   20.100842  24.147627  10.21256
 25.064299  48.283043  20.977459  23.265625  20.141813  11.87677
 17.84212   15.1286955 14.9789295 23.502743  16.092314  21.276255
 26.55347   16.940031  23.485325  14.927286  20.90435   19.254526
 24.397417  27.566774  23.607512  17.905067  22.675825  25.12203
 15.141896  18.460642  23.440636  16.4928    23.372946  30.389936
 15.330368  24.69199   17.316717  14.531138  10.496169  24.805672
 15.659789  38.916733  20.403166  42.113743   8.544421  22.536352
 15.654481  15.709977  17.263374  23.888586  21.690222  46.16276
 15.304819  31.137545  25.326769  18.969254  26.29209   11.722559
 40.65201   20.52522   17.135836  24.829275  15.565665  23.360205
  8.280649  24.018639  19.57025   20.865868  23.611485  22.455328
 17.646477  17.687094  14.59732   25.61237   13.333718  22.577513
 20.657572  14.8804865 16.539358  23.276703  24.873934  22.52675
 23.107155  31.871576  19.262531  19.536154  28.251024  23.817226
 12.874959  22.59372   12.234834  10.024989  20.419611  10.369816
 45.84478   24.873934  12.357825  16.367088  14.355771  28.338346
 18.669233  20.334248  10.546778  21.30952   21.00914   20.669264
 23.91886   25.009733  26.945326  13.288843  18.277857  20.95568
 18.233625  23.807056  13.400126  23.875198  33.050533  27.785492
 25.296518  19.071947  20.950756  11.507434  22.855497  15.573306
 22.33747   20.807749  22.41908   17.212593  12.645366  35.121113
 18.852188  48.823723  22.462465  24.267456  21.375692  19.38756
  8.561088  20.726429  23.400837  21.41578   17.63176   25.232733
 21.164701  26.444288  14.49171   49.559753  30.693232  23.20531
 22.950115  16.84211   30.982431  16.259336  23.613512  20.93225
 20.178421  22.782583 ]
```

In [30]:

```
# R squared error
score_1 = metrics.r2_score(Y_train, training_data_prediction)

# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_train, training_data_prediction)

print("R squared error : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared error :  0.9733349094832763
```

```
R squared error :  0.97553490594852705
Mean Absolute Error :  1.145314053261634
```

In [31]:

```python
# Visualizing the actual Prices and predicted prices

plt.scatter(Y_train, training_data_prediction)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual Price vs Preicted Price")
plt.show()
```

Prediction on Test Data

In [32]:

```python
# accuracy for prediction on test data
test_data_prediction = model.predict(X_test)
```

In [34]:

```python
# R squared error
score_1 = metrics.r2_score(Y_test, test_data_prediction)
# Mean Absolute Error
score_2 = metrics.mean_absolute_error(Y_test, test_data_prediction)

print("R squared error : ", score_1)
print('Mean Absolute Error : ', score_2)
```

```
R squared error :  0.9115937697657654
Mean Absolute Error :  1.9922956859364223
```

In [ ]:

```python

```