In [1]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
import pandas as pd

# Load the dataset
file_path = 'final_dataset.csv'
data = pd.read_csv(file_path)

# Display the first few rows and the summary statistics of the dataset
data_head = data.head()
data_description = data.describe(include='all')
data_info = data.info()

data_head, data_description, data_info
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5407 entries, 0 to 5406
Data columns (total 1 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Date;Price;Open;High;Low;Vol.;Change %;GDPC1_PCH;DFF;Price_USD;Change %_USD;UNRATE;INDPRO;T10YIE;Production_Oil
5407 non-null   object
dtypes: object(1)
memory usage: 42.4+ KB
```

Out[2]:
```
(   Date;Price;Open;High;Low;Vol.;Change %;GDPC1_PCH;DFF;Price_USD;Change %_USD;UNRATE;INDPRO;T10YIE;Production_Oil
 0  2003-01-02;31.85;31.6;32.09;31.4;62.48K;2.08%;...
 1  2003-01-03;33.08;31.98;33.25;31.9;68.42K;3.86%...
 2  2003-01-06;32.1;33.08;33.33;31.91;98.25K;-2.96...
 3  2003-01-07;31.08;32.11;32.4;30.51;124.28K;-3.1...
 4  2003-01-08;30.56;31.05;31.3;29.75;108.04K;-1.6...                                                         ,
        Date;Price;Open;High;Low;Vol.;Change %;GDPC1_PCH;DFF;Price_USD;Change %_USD;UNRATE;INDPRO;T10YIE;Production_O
il
 count                                               5407
 unique                                              5407
 top     2003-01-02;31.85;31.6;32.09;31.4;62.48K;2.08%;...
 freq                                                   1
,
 None)
```

In [3]:
```
# Split the data into separate columns
data = pd.read_csv(file_path, delimiter=';')

# Display the first few rows and summary statistics again
data_head = data.head()
data_description = data.describe(include='all')
data_info = data.info()

data_head, data_description, data_info
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5407 entries, 0 to 5406
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Date            5407 non-null   object 
 1   Price           5407 non-null   float64
 2   Open            5407 non-null   float64
 3   High            5407 non-null   float64
 4   Low             5407 non-null   float64
 5   Vol.            5259 non-null   object 
 6   Change %        5407 non-null   object 
 7   GDPC1_PCH       5407 non-null   float64
 8   DFF             5407 non-null   float64
 9   Price_USD       5361 non-null   float64
 10  Change %_USD    5361 non-null   float64
 11  UNRATE          5407 non-null   float64
 12  INDPRO          5407 non-null   float64
 13  T10YIE          5243 non-null   float64
 14  Production_Oil  5407 non-null   float64
dtypes: float64(12), object(3)
memory usage: 633.8+ KB
```

Out[3]:
```
(          Date  Price   Open   High    Low     Vol. Change %  GDPC1_PCH   DFF  \
 0  2003-01-02  31.85  31.60  32.09  31.40   62.48K    2.08%   -0.30972  1.30
 1  2003-01-03  33.08  31.98  33.25  31.90   68.42K    3.86%   -0.30972  1.12
 2  2003-01-06  32.10  33.08  33.33  31.91   98.25K   -2.96%   -0.30972  1.22
 3  2003-01-07  31.08  32.11  32.40  30.51  124.28K   -3.18%   -0.30972  1.20
 4  2003-01-08  30.56  31.05  31.30  29.75  108.04K   -1.67%   -0.30972  1.29

    Price_USD  Change %_USD  UNRATE   INDPRO  T10YIE  Production_Oil
 0     102.98        0.0111     5.8  91.1355    1.64        178412.0
 1     102.47       -5.0000     5.8  91.1355    1.62        178412.0
 2     101.97       -0.0049     5.8  91.1355    1.63        178412.0
 3     102.57        0.0059     5.8  91.1355    1.62        178412.0
 4     101.87       -0.0068     5.8  91.1355    1.71        178412.0  ,
               Date        Price         Open         High          Low   Vol.  \
 count         5407  5407.000000  5407.000000  5407.000000  5407.000000   5259
 unique        5407          NaN          NaN          NaN          NaN   5004
 top     2003-01-02          NaN          NaN          NaN          NaN  1.01M
 freq             1          NaN          NaN          NaN          NaN      7
 mean           NaN    68.242343    68.254570    69.295735    67.125756    NaN
 std            NaN    23.348724    23.330241    23.551942    23.091089    NaN
 min            NaN   -37.630000   -14.000000    13.690000   -40.320000    NaN
 25%            NaN    49.855000    49.800000    50.760000    49.050000    NaN
 50%            NaN    66.120000    66.050000    66.920000    64.990000    NaN
 75%            NaN    86.660000    86.565000    87.905000    85.420000    NaN
 max            NaN   145.290000   145.190000   147.270000   143.220000    NaN

        Change %    GDPC1_PCH          DFF    Price_USD  Change %_USD  \
 count      5407  5407.000000  5407.000000  5361.000000   5361.000000
 unique     1109          NaN          NaN          NaN           NaN
 top      -0.46%          NaN          NaN          NaN           NaN
 freq         20          NaN          NaN          NaN           NaN
 mean        NaN     4.449240     1.476079    89.311809     -0.001676
 std         NaN    40.021468     1.730534     8.914388      1.337539
 min         NaN    -8.720690     0.040000    71.330000    -18.000000
 25%         NaN    -0.633850     0.120000    81.330000     -0.003100
 50%         NaN    -0.029040     0.660000    89.660000      0.000000
 75%         NaN     0.535250     2.290000    96.520000      0.003100
 max         NaN   364.000000     5.410000   114.110000     16.000000

              UNRATE       INDPRO       T10YIE  Production_Oil
 count   5407.000000  5407.000000  5243.000000     5407.000000
 unique          NaN          NaN          NaN             NaN
 top             NaN          NaN          NaN             NaN
 freq            NaN          NaN          NaN             NaN
```

```
mean       5.873608   98.005575    2.082701   247130.266321
std        2.047201    4.601700    0.408154    85636.250741
min        3.400000   84.597900    0.040000   119208.000000
25%        4.400000   95.272900    1.830000   166810.000000
50%        5.300000   99.042700    2.180000   233562.000000
75%        7.200000  101.682000    2.370000   324443.000000
max       14.800000  104.118100    3.020000   412155.000000  ,
None)
```

In [4]:

```
# Convert 'Date' to datetime format
data['Date'] = pd.to_datetime(data['Date'])

# Removing '%' from 'Change %' and converting to float
data['Change %'] = data['Change %'].str.rstrip('%').astype('float') / 100


# Rename the 'Vol.' column to 'Vol'
data = data.rename(columns={'Vol.': 'Vol'})
```

In [5]:

```
# Define a function to convert volume strings to numeric values, handling both 'K' and 'M'
def convert_volume(vol):
    if pd.isna(vol):
        return None  # Return None for missing values
    if 'K' in vol:
        return float(vol.rstrip('K')) * 1000
    elif 'M' in vol:
        return float(vol.rstrip('M')) * 1000000
    return float(vol)

# Apply the conversion function to the 'Vol.' column
data['Vol'] = data['Vol'].apply(convert_volume)

# Check the data types and first few rows again
data_info = data.info()
data_head = data.head()

data_info, data_head
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5407 entries, 0 to 5406
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Date            5407 non-null   datetime64[ns]
 1   Price           5407 non-null   float64
 2   Open            5407 non-null   float64
 3   High            5407 non-null   float64
 4   Low             5407 non-null   float64
 5   Vol             5259 non-null   float64
 6   Change %        5407 non-null   float64
 7   GDPC1_PCH       5407 non-null   float64
 8   DFF             5407 non-null   float64
 9   Price_USD       5361 non-null   float64
 10  Change %_USD    5361 non-null   float64
 11  UNRATE          5407 non-null   float64
 12  INDPRO          5407 non-null   float64
 13  T10YIE          5243 non-null   float64
 14  Production_Oil  5407 non-null   float64
dtypes: datetime64[ns](1), float64(14)
memory usage: 633.8 KB
```

Out[5]:

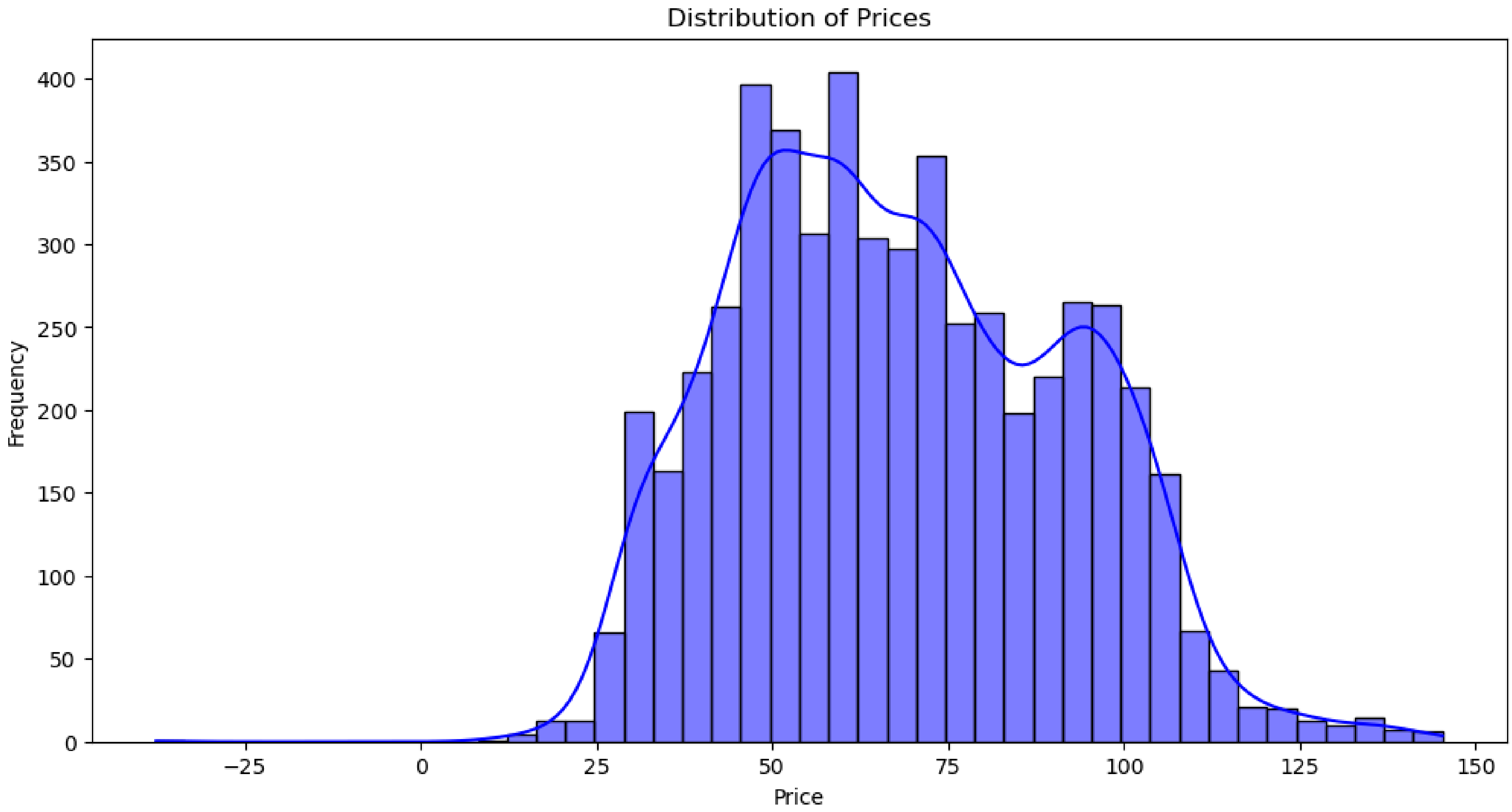
```
(None,
         Date  Price   Open   High    Low       Vol  Change %  GDPC1_PCH   DFF  \
 0 2003-01-02  31.85  31.60  32.09  31.40   62480.0    0.0208   -0.30972  1.30
 1 2003-01-03  33.08  31.98  33.25  31.90   68420.0    0.0386   -0.30972  1.12
 2 2003-01-06  32.10  33.08  33.33  31.91   98250.0   -0.0296   -0.30972  1.22
 3 2003-01-07  31.08  32.11  32.40  30.51  124280.0   -0.0318   -0.30972  1.20
 4 2003-01-08  30.56  31.05  31.30  29.75  108040.0   -0.0167   -0.30972  1.29

    Price_USD  Change %_USD  UNRATE   INDPRO  T10YIE  Production_Oil
 0     102.98        0.0111     5.8  91.1355    1.64        178412.0
 1     102.47       -5.0000     5.8  91.1355    1.62        178412.0
 2     101.97       -0.0049     5.8  91.1355    1.63        178412.0
 3     102.57        0.0059     5.8  91.1355    1.62        178412.0
 4     101.87       -0.0068     5.8  91.1355    1.71        178412.0  )
```

In [6]:

```
# Calculate the percentage of missing values for each column
nan_percentages = data.isna().sum() / len(data) * 100
nan_percentages
```

Out[6]:
```
Date              0.000000
Price             0.000000
Open              0.000000
High              0.000000
Low               0.000000
Vol               2.737193
Change %          0.000000
GDPC1_PCH         0.000000
DFF               0.000000
Price_USD         0.850749
Change %_USD      0.850749
UNRATE            0.000000
INDPRO            0.000000
T10YIE            3.033105
Production_Oil    0.000000
dtype: float64
```

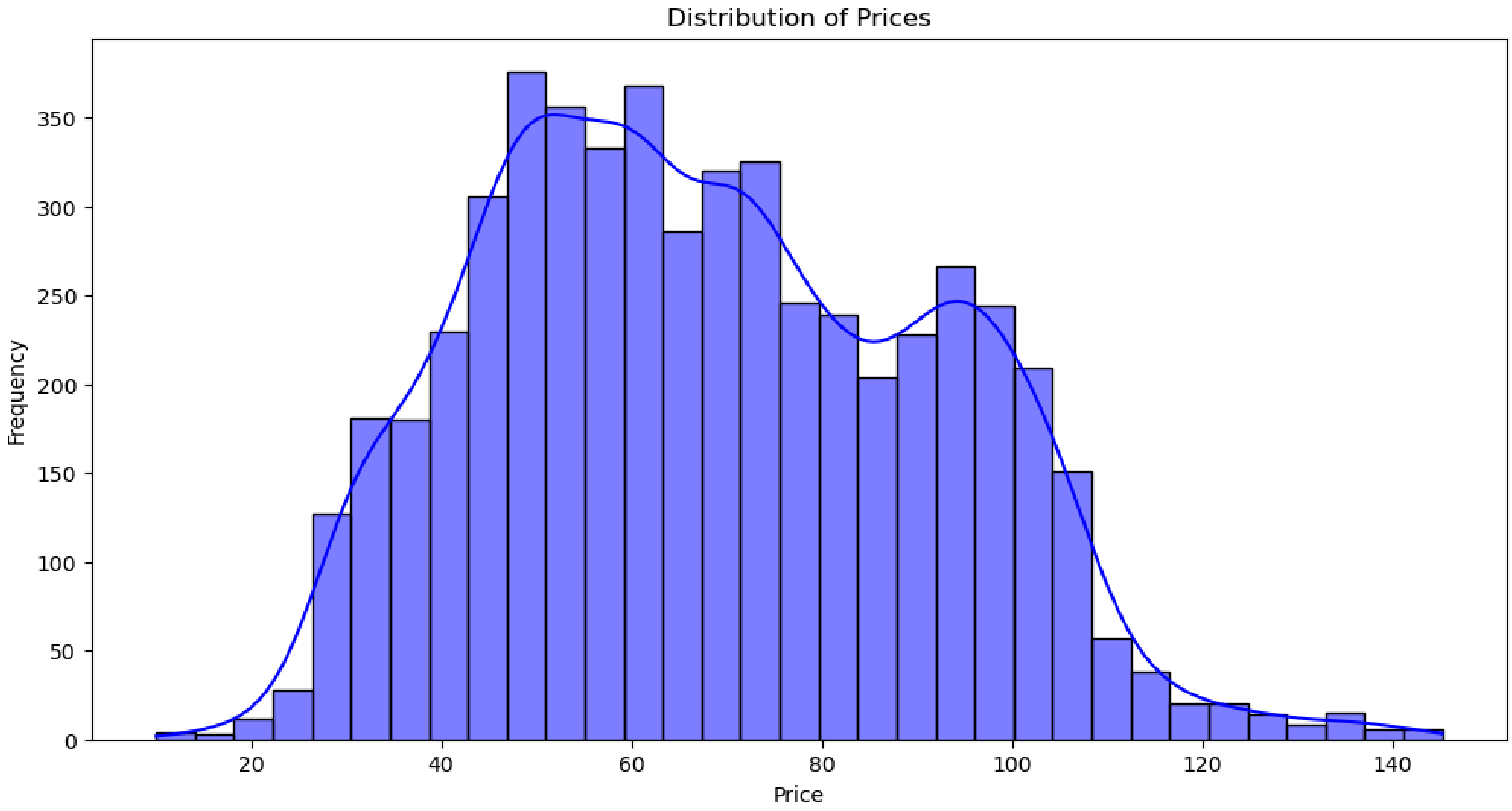
In [7]:
```
import seaborn as sns
import matplotlib.pyplot as plt


plt.figure(figsize=(12, 6))
sns.histplot(data['Price'], kde=True, color='blue')
plt.title('Distribution of Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```



In [8]:
```
# Assuming the negative value is in the 'Price' column
data = data[data['Price'] >= 0]
```

In [9]:
```
import seaborn as sns
import matplotlib.pyplot as plt


plt.figure(figsize=(12, 6))
sns.histplot(data['Price'], kde=True, color='blue')
plt.title('Distribution of Prices')
plt.xlabel('Price')
```

```
plt.ylabel('Frequency')
plt.show()
```



In [10]:
```
import numpy as np
# Function to fill missing values based on described logic
def fill_with_median(df, column):
    for i in df[df[column].isna()].index:
        # Find indices for most recent non-missing values before and after the NaN
        previous_index = df[column].iloc[:i].last_valid_index()
        next_index = df[column].iloc[i+1:].first_valid_index()

        if pd.notna(previous_index) and pd.notna(next_index):
```

```
            # Compute median of the two values
            median_value = np.median([df.at[previous_index, column], df.at[next_index, column]])
            df.at[i, column] = median_value  # Fill missing value with the median

# Apply the function to each column except 'Time' as it likely doesn't have missing values
for column in data.columns.drop('Date'):
    fill_with_median(data, column)

print(data[:])
```

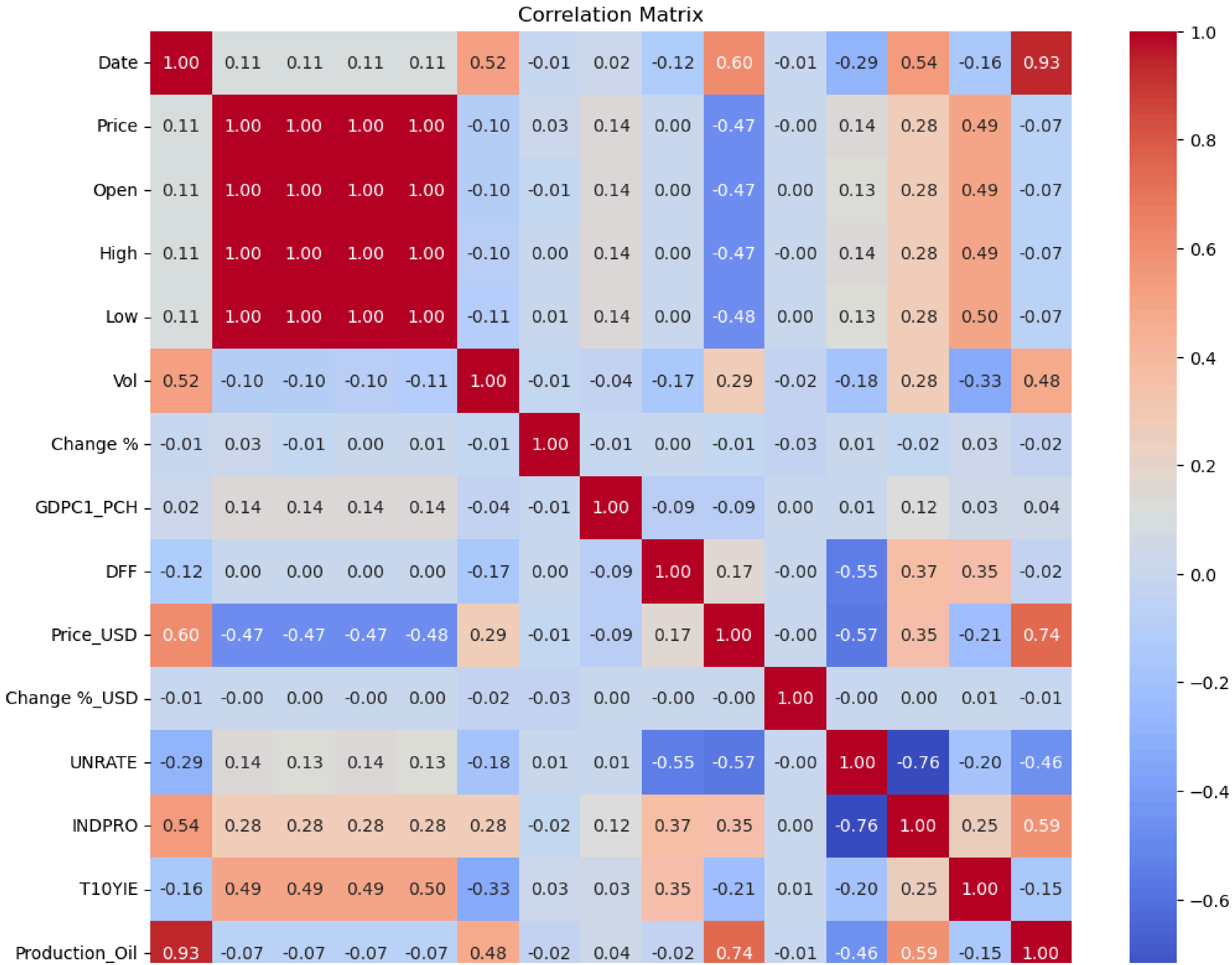
```
           Date  Price   Open   High    Low       Vol  Change %  GDPC1_PCH  \
0    2003-01-02  31.85  31.60  32.09  31.40   62480.0    0.0208   -0.30972   
1    2003-01-03  33.08  31.98  33.25  31.90   68420.0    0.0386   -0.30972   
2    2003-01-06  32.10  33.08  33.33  31.91   98250.0   -0.0296   -0.30972   
3    2003-01-07  31.08  32.11  32.40  30.51  124280.0   -0.0318   -0.30972   
4    2003-01-08  30.56  31.05  31.30  29.75  108040.0   -0.0167   -0.30972   
...         ...    ...    ...    ...    ...       ...       ...        ...   
5402 2023-12-25  73.79  73.49  73.94  73.48  237960.0    0.0031    0.20298   
5403 2023-12-26  75.57  73.56  76.18  73.13  208720.0    0.0241    0.20298   
5404 2023-12-27  74.11  75.32  75.66  73.77  253320.0   -0.0193    0.20298   
5405 2023-12-28  71.77  73.80  74.40  71.72  262750.0   -0.0316    0.20298   
5406 2023-12-29  71.65  71.99  72.62  71.25  214490.0   -0.0017    0.20298   

       DFF  Price_USD  Change %_USD  UNRATE    INDPRO  T10YIE  Production_Oil  
0     1.30    102.980       0.01110     5.8   91.1355    1.64        178412.0  
1     1.12    102.470      -5.00000     5.8   91.1355    1.62        178412.0  
2     1.22    101.970      -0.00490     5.8   91.1355    1.63        178412.0  
3     1.20    102.570       0.00590     5.8   91.1355    1.62        178412.0  
4     1.29    101.870      -0.00680     5.8   91.1355    1.71        178412.0  
...    ...        ...           ...     ...       ...     ...             ...  
5402  5.33    101.345      -0.00305     3.7  102.6149    2.17        412155.0  
5403  5.33    101.470      -0.00240     3.7  102.6149    2.18        412155.0  
5404  5.33    100.990      -0.00470     3.7  102.6149    2.15        412155.0  
5405  5.33    101.230       0.00240     3.7  102.6149    2.16        412155.0  
5406  5.33    101.330       1.00000     3.7  102.6149    2.16        412155.0  

[5406 rows x 15 columns]
```

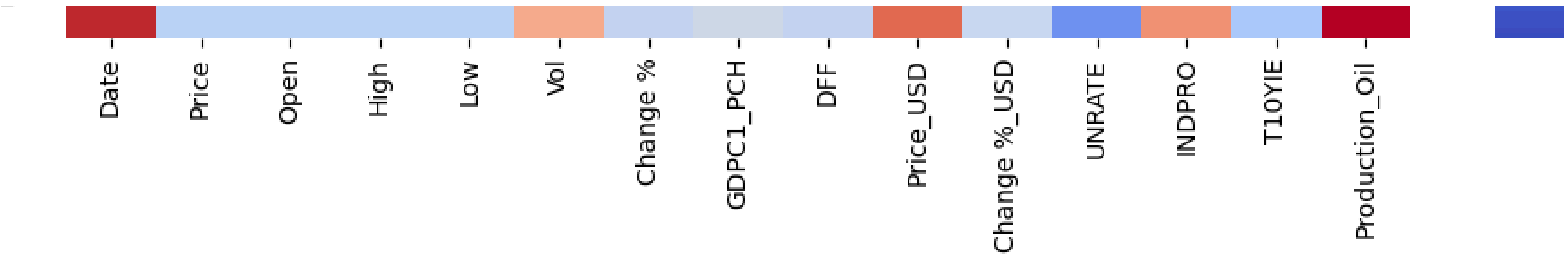
In [11]:

```
# Check for missing values in the dataset
missing_values = data.isnull().sum()
missing_values
```

Out[11]:
```
Date              0
Price             0
Open              0
High              0
Low               0
Vol               0
Change %          0
GDPC1_PCH         0
DFF               0
Price_USD         0
Change %_USD      0
UNRATE            0
INDPRO            0
T10YIE            0
Production_Oil    0
dtype: int64
```

In [12]:
```
import matplotlib.pyplot as plt
import seaborn as sns
# Calculating the correlation matrix
correlation_matrix = data.corr()

# Plotting the correlation matrix using seaborn
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
Date 1.00 0.11 0.11 0.11 0.11 0.52 -0.01 0.02 -0.12 0.60 -0.01 -0.29 0.54 -0.16 0.93
Price 0.11 1.00 1.00 1.00 1.00 -0.10 0.03 0.14 0.00 -0.47 -0.00 0.14 0.28 0.49 -0.07
Open 0.11 1.00 1.00 1.00 1.00 -0.10 -0.01 0.14 0.00 -0.47 0.00 0.13 0.28 0.49 -0.07
High 0.11 1.00 1.00 1.00 1.00 -0.10 0.00 0.14 0.00 -0.47 -0.00 0.14 0.28 0.49 -0.07
Low 0.11 1.00 1.00 1.00 1.00 -0.11 0.01 0.14 0.00 -0.48 0.00 0.13 0.28 0.50 -0.07
Vol 0.52 -0.10 -0.10 -0.10 -0.11 1.00 -0.01 -0.04 -0.17 0.29 -0.02 -0.18 0.28 -0.33 0.48
Change % -0.01 0.03 -0.01 0.00 0.01 -0.01 1.00 -0.01 0.00 -0.01 -0.03 0.01 -0.02 0.03 -0.02
GDPC1_PCH 0.02 0.14 0.14 0.14 0.14 -0.04 -0.01 1.00 -0.09 -0.09 0.00 0.01 0.12 0.03 0.04
DFF -0.12 0.00 0.00 0.00 0.00 -0.17 0.00 -0.09 1.00 0.17 -0.00 -0.55 0.37 0.35 -0.02
Price_USD 0.60 -0.47 -0.47 -0.47 -0.48 0.29 -0.01 -0.09 0.17 1.00 -0.00 -0.57 0.35 -0.21 0.74
Change %_USD -0.01 -0.00 0.00 -0.00 0.00 -0.02 -0.03 0.00 -0.00 -0.00 1.00 -0.00 0.00 0.01 -0.01
UNRATE -0.29 0.14 0.13 0.14 0.13 -0.18 0.01 0.01 -0.55 -0.57 -0.00 1.00 -0.76 -0.20 -0.46
INDPRO 0.54 0.28 0.28 0.28 0.28 0.28 -0.02 0.12 0.37 0.35 0.00 -0.76 1.00 0.25 0.59
T10YIE -0.16 0.49 0.49 0.49 0.50 -0.33 0.03 0.03 0.35 -0.21 0.01 -0.20 0.25 1.00 -0.15
Production_Oil 0.93 -0.07 -0.07 -0.07 -0.07 0.48 -0.02 0.04 -0.02 0.74 -0.01 -0.46 0.59 -0.15 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6



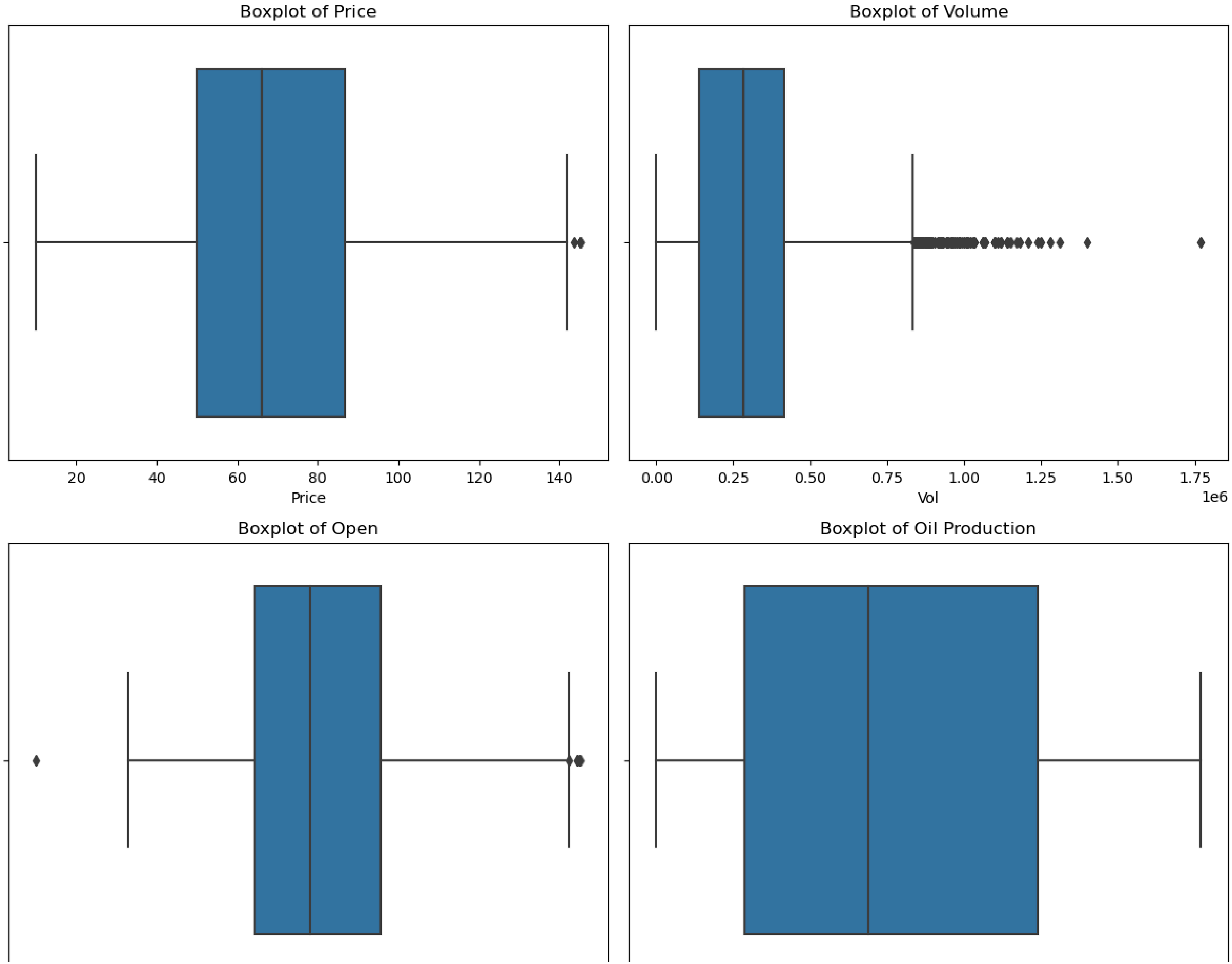
In [13]:
```
data.head()
```

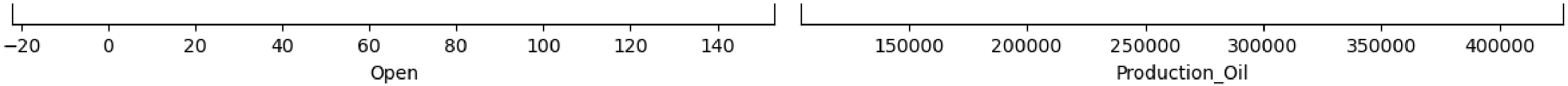
Out[13]:

	Date	Price	Open	High	Low	Vol	Change %	GDPC1_PCH	DFF	Price_USD	Change %_USD	UNRATE	INDPRO	T10YIE	Production_Oil
0	2003-01-02	31.85	31.60	32.09	31.40	62480.0	0.0208	-0.30972	1.30	102.98	0.0111	5.8	91.1355	1.64	178412.0
1	2003-01-03	33.08	31.98	33.25	31.90	68420.0	0.0386	-0.30972	1.12	102.47	-5.0000	5.8	91.1355	1.62	178412.0
2	2003-01-06	32.10	33.08	33.33	31.91	98250.0	-0.0296	-0.30972	1.22	101.97	-0.0049	5.8	91.1355	1.63	178412.0
3	2003-01-07	31.08	32.11	32.40	30.51	124280.0	-0.0318	-0.30972	1.20	102.57	0.0059	5.8	91.1355	1.62	178412.0
4	2003-01-08	30.56	31.05	31.30	29.75	108040.0	-0.0167	-0.30972	1.29	101.87	-0.0068	5.8	91.1355	1.71	178412.0

In [14]:
```
# Descriptive statistics for key columns to check for negative values
descriptive_stats = data[['Price', 'Vol', 'Open', 'High', 'Low', 'Production_Oil']].describe()

# Plotting boxplots for price and volume to visualize outliers
fig, ax = plt.subplots(2, 2, figsize=(12, 10))
sns.boxplot(data=data, x='Price', ax=ax[0, 0])
ax[0, 0].set_title('Boxplot of Price')

sns.boxplot(data=data, x='Vol', ax=ax[0, 1])
ax[0, 1].set_title('Boxplot of Volume')

sns.boxplot(data=data, x='Open', ax=ax[1, 0])
ax[1, 0].set_title('Boxplot of Open')

sns.boxplot(data=data, x='Production_Oil', ax=ax[1, 1])
```

```
ax[1, 1].set_title('Boxplot of Oil Production')

plt.tight_layout()
plt.show()

descriptive_stats
```


Boxplot of Price
20
40
60
80
100
120
140
Price
Boxplot of Volume
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
Vol
Boxplot of Open
Boxplot of Oil Production



Out[14]:

	Price	Vol	Open	High	Low	Production_Oil
count	5406.000000	5.406000e+03	5406.000000	5406.000000	5406.000000	5406.000000
mean	68.261927	3.157299e+05	68.263916	69.305252	67.145631	247109.884018
std	23.306428	2.145347e+05	23.322274	23.543722	23.046925	85631.054894
min	10.010000	2.000000e+01	-14.000000	13.690000	-16.740000	119208.000000
25%	49.880000	1.383225e+05	49.805000	50.780000	49.065000	166810.000000
50%	66.125000	2.818550e+05	66.050000	66.925000	64.995000	233562.000000
75%	86.660000	4.169250e+05	86.567500	87.907500	85.420000	324443.000000
max	145.290000	1.770000e+06	145.190000	147.270000	143.220000	412155.000000

In [15]:

```
# Remove 'Open', 'High', 'Low' columns from the dataset
data_cleaned = data.drop(columns=['Open','High', 'Low'])

# Verify the changes
print(data_cleaned.describe())
data_cleaned.head()
```

```
                                 Date       Price           Vol     Change %  \
count                            5406  5406.000000  5.406000e+03  5406.000000
mean   2013-08-19 11:49:04.728079872    68.261927  3.157299e+05     0.000370
min              2003-01-02 00:00:00    10.010000  2.000000e+01    -1.266000
25%              2008-05-22 06:00:00    49.880000  1.383225e+05    -0.012100
50%              2013-09-26 12:00:00    66.125000  2.818550e+05     0.001100
75%              2018-11-18 06:00:00    86.660000  4.169250e+05     0.013100
max              2023-12-29 00:00:00   145.290000  1.770000e+06     0.376600
std                               NaN   23.306428  2.145347e+05     0.031337

         GDPC1_PCH          DFF    Price_USD  Change %_USD       UNRATE  \
count  5406.000000  5406.000000  5406.000000   5406.000000  5406.000000
mean      4.451677     1.476343    89.383627      0.001024     5.871957
min      -8.720690     0.040000    71.330000    -18.000000     3.400000
25%      -0.633850     0.120000    81.382500     -0.003012     4.400000
50%      -0.029040     0.660000    89.760000      0.000000     5.300000
75%       0.535250     2.290000    96.550000      0.003100     7.200000
max     364.000000     5.410000   114.110000     16.000000    14.800000
std      40.024769     1.730586     8.923588      1.336380     2.043787

            INDPRO       T10YIE  Production_Oil
count  5406.000000  5406.000000     5406.000000
mean     98.008055     2.080292   247109.884018
min      84.597900     0.040000   119208.000000
25%      95.272900     1.820000   166810.000000
50%      99.042700     2.170000   233562.000000
75%     101.684700     2.360000   324443.000000
max     104.118100     3.020000   412155.000000
std       4.598511     0.406826    85631.054894
```

Out[15]:

	Date	Price	Vol	Change %	GDPC1_PCH	DFF	Price_USD	Change %_USD	UNRATE	INDPRO	T10YIE	Production_Oil
0	2003-01-02	31.85	62480.0	0.0208	-0.30972	1.30	102.98	0.0111	5.8	91.1355	1.64	178412.0
1	2003-01-03	33.08	68420.0	0.0386	-0.30972	1.12	102.47	-5.0000	5.8	91.1355	1.62	178412.0
2	2003-01-06	32.10	98250.0	-0.0296	-0.30972	1.22	101.97	-0.0049	5.8	91.1355	1.63	178412.0
3	2003-01-07	31.08	124280.0	-0.0318	-0.30972	1.20	102.57	0.0059	5.8	91.1355	1.62	178412.0
4	2003-01-08	30.56	108040.0	-0.0167	-0.30972	1.29	101.87	-0.0068	5.8	91.1355	1.71	178412.0

In [16]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(14, 7))
```

```
plt.subplot(2, 1, 1)
plt.plot(data_cleaned['Date'], data_cleaned['Price'], label='Price')
plt.title('Price Trend Over Time')
plt.xlabel('Date')
plt.ylabel('Price')

plt.subplot(2, 1, 2)
plt.plot(data_cleaned['Date'], data_cleaned['Vol'], label='Volume', color='orange')
plt.title('Volume Trend Over Time')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.tight_layout()
plt.show()
```

In [17]:
```
# Print details about negative values in each column except the first one
negative_details = {}  # Dictionary to store results

# Detailed check for negative values in each column
for column in data_cleaned.columns[1:]:
    count_neg = (data_cleaned[column] < 0).sum()
    if count_neg > 0:
        negative_details[column] = count_neg


# Check if there are any entries in the dictionary and print them
if negative_details:
    print("Columns with negative values and their counts:")
    for col, count in negative_details.items():
        print(f'Column "{col}" has {count} negative values')
else:
    print("No negative values found in the columns checked.")
```

```
Columns with negative values and their counts:
Column "Change %" has 2564 negative values
Column "GDPC1_PCH" has 2769 negative values
Column "Change %_USD" has 2634 negative values
```

In [18]:
```
# Creating lagged features for Price and Volume
data_cleaned['Volume_Lag1'] = data_cleaned['Vol'].shift(1)
data_cleaned['Price_Lag1'] = data_cleaned['Price'].shift(1)


# Calculating rolling window statistics for Price
window_sizes = [7, 30, 90]  # Weekly, Monthly, Quarterly windows
for window in window_sizes:
    data_cleaned[f'Price_RollingMean_{window}'] = data_cleaned['Price'].rolling(window=window).mean()
    data_cleaned[f'Price_RollingStd_{window}'] = data_cleaned['Price'].rolling(window=window).std()

# Compute rate of change for Price
data_cleaned['Price_RateOfChange'] = data_cleaned['Price'].pct_change()

# Display the new features and their first few rows to confirm creation
data_cleaned[['Date', 'Price', 'Price_Lag1','Volume_Lag1', 'Price_RateOfChange'] +
           [col for col in data_cleaned.columns if 'Rolling' in col]].head(10)
```

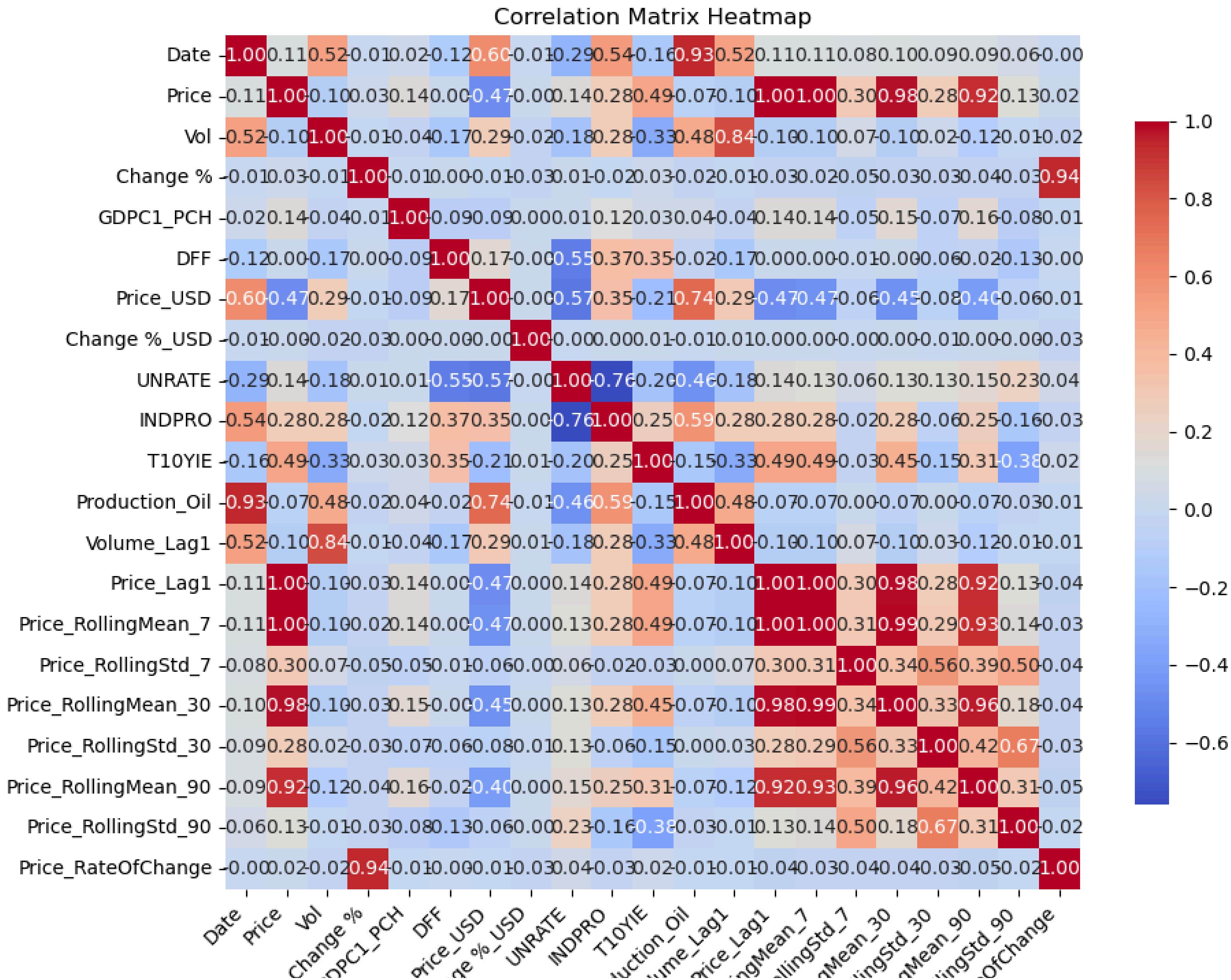
Out[18]:

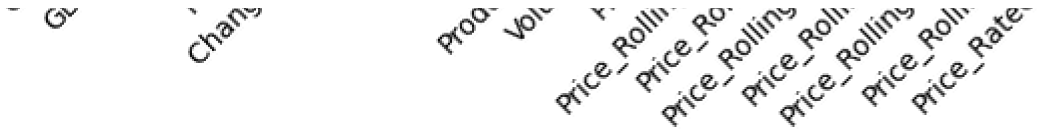
	Date	Price	Price_Lag1	Volume_Lag1	Price_RateOfChange	Price_RollingMean_7	Price_RollingStd_7	Price_RollingMean_30	Price_RollingS
0	2003-01-02	31.85	NaN	NaN	NaN	NaN	NaN	NaN	
1	2003-01-03	33.08	31.85	62480.0	0.038619	NaN	NaN	NaN	
2	2003-01-06	32.10	33.08	68420.0	-0.029625	NaN	NaN	NaN	
3	2003-01-07	31.08	32.10	98250.0	-0.031776	NaN	NaN	NaN	
4	2003-01-08	30.56	31.08	124280.0	-0.016731	NaN	NaN	NaN	
5	2003-01-09	31.99	30.56	108040.0	0.046793	NaN	NaN	NaN	
6	2003-01-10	31.68	31.99	111720.0	-0.009691	31.762857	0.798722	NaN	
7	2003-01-13	32.26	31.68	98560.0	0.018308	31.821429	0.820903	NaN	
8	2003-01-14	32.37	32.26	90730.0	0.003410	31.720000	0.669353	NaN	
9	2003-01-15	33.21	32.37	114000.0	0.025950	31.878571	0.874441	NaN	

In [19]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming data_cleaned is your DataFrame
# Calculate the correlation matrix
corr_matrix = data_cleaned.corr()

# Set up the matplotlib figure
plt.figure(figsize=(10, 8))

# Generate a heatmap
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm',
            cbar_kws={'shrink': .8}, square=True)
```

```
# Adding labels
plt.title('Correlation Matrix Heatmap')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)

# Show plot
plt.tight_layout()
plt.show()
```


Correlation Matrix Heatmap
Date
Price
Vol
Change %
GDPC1_PCH
DFF
Price_USD
Change %_USD
UNRATE
INDPRO
T10YIE
Production_Oil
Volume_Lag1
Price_Lag1
Price_RollingMean_7
Price_RollingStd_7
Price_RollingMean_30
Price_RollingStd_30
Price_RollingMean_90
Price_RollingStd_90
Price_RateOfChange



In [21]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.preprocessing import MinMaxScaler
import time


import pandas as pd


# Normalize multiple features
features = ['Vol','Change %','GDPC1_PCH','DFF','Price_USD','Change %_USD','UNRATE','INDPRO','T10YIE','Production_Oil',
target = 'Price'  # Replace with your target variable
feature_scaler = MinMaxScaler(feature_range=(0, 1))
target_scaler = MinMaxScaler(feature_range=(0, 1))

data_cleaned[features] = feature_scaler.fit_transform(data_cleaned[features])
data_cleaned[target] = target_scaler.fit_transform(data_cleaned[[target]])

data_cleaned = data_cleaned.set_index('Date')  # Set 'Date' as the index

# Skip the first 90 days in the dataset
start_index = 90
data_filtered = data_cleaned[start_index:]

# Find the last date in your dataset
last_date = data_filtered.index.max()

# Calculate the start of the last month from the last date
last_month_start = last_date - pd.DateOffset(months=1)

train_data = data_filtered[data_filtered.index < last_month_start]
test_data = data_filtered[data_filtered.index >= last_month_start]

# Split data into features and target for training and testing sets
X_train = train_data[features]
```

```
y_train = train_data[target]
X_test = test_data[features]
y_test = test_data[target]
```

In [22]:
```
train_data
```

Out[22]:

Date	Price	Vol	Change %	GDPC1_PCH	DFF	Price_USD	Change %_USD	UNRATE	INDPRO	T10YIE	Production_Oil	Volume_La
2003-05-13	0.136679	0.046611	0.796299	0.024130	0.221601	0.546751	0.529465	0.236842	0.297610	0.553691	0.19239	0.0519
2003-05-14	0.141632	0.054809	0.785036	0.024130	0.234637	0.543478	0.529368	0.236842	0.297610	0.543624	0.19239	0.046
2003-05-15	0.138454	0.047549	0.761780	0.024130	0.245810	0.558439	0.529612	0.236842	0.297610	0.546980	0.19239	0.0548
2003-05-16	0.141410	0.032492	0.779192	0.024130	0.227188	0.531791	0.176471	0.236842	0.297610	0.530201	0.19239	0.0475
2003-05-19	0.139119	0.041707	0.764276	0.024130	0.227188	0.524778	0.529318	0.236842	0.297610	0.526846	0.19239	0.0324
...	...	...	...	...	...	...	...	...	...	...	...	
2023-11-22	0.495934	0.219952	0.765494	0.023942	0.985102	0.761805	0.529512	0.026316	0.939555	0.744966	0.95461	0.1348
2023-11-23	0.490316	0.191768	0.764702	0.023942	0.985102	0.758298	0.529368	0.026316	0.939555	0.736577	0.95461	0.2199
2023-11-24	0.484403	0.158832	0.764337	0.023942	0.985102	0.749649	0.529309	0.026316	0.939555	0.744966	0.95461	0.1917
2023-11-27	0.479376	0.163584	0.765250	0.023942	0.985102	0.744974	0.470588	0.026316	0.939555	0.728188	0.95461	0.1588
2023-11-28	0.490834	0.161923	0.783331	0.023942	0.985102	0.734455	0.529282	0.026316	0.939555	0.731544	0.95461	0.1635

5293 rows × 20 columns

In [23]:
```
X_train
```

Out[23]:

	Vol	Change %	GDPC1_PCH	DFF	Price_USD	Change %_USD	UNRATE	INDPRO	T10YIE	Production_Oil	Price_Lag1	Volume_L
Date												
2003-05-13	0.046611	0.796299	0.024130	0.221601	0.546751	0.529465	0.236842	0.297610	0.553691	0.19239	0.128179	0.051
2003-05-14	0.054809	0.785036	0.024130	0.234637	0.543478	0.529368	0.236842	0.297610	0.543624	0.19239	0.136679	0.04
2003-05-15	0.047549	0.761780	0.024130	0.245810	0.558439	0.529612	0.236842	0.297610	0.546980	0.19239	0.141632	0.054
2003-05-16	0.032492	0.779192	0.024130	0.227188	0.531791	0.176471	0.236842	0.297610	0.530201	0.19239	0.138454	0.047
2003-05-19	0.041707	0.764276	0.024130	0.227188	0.524778	0.529318	0.236842	0.297610	0.526846	0.19239	0.141410	0.032
...	...	...	...	...	...	...	...	...	...	...	...	
2023-11-22	0.219952	0.765494	0.023942	0.985102	0.761805	0.529512	0.026316	0.939555	0.744966	0.95461	0.500887	0.134
2023-11-23	0.191768	0.764702	0.023942	0.985102	0.758298	0.529368	0.026316	0.939555	0.736577	0.95461	0.495934	0.219
2023-11-24	0.158832	0.764337	0.023942	0.985102	0.749649	0.529309	0.026316	0.939555	0.744966	0.95461	0.490316	0.191
2023-11-27	0.163584	0.765250	0.023942	0.985102	0.744974	0.470588	0.026316	0.939555	0.728188	0.95461	0.484403	0.158
2023-11-28	0.161923	0.783331	0.023942	0.985102	0.734455	0.529282	0.026316	0.939555	0.731544	0.95461	0.479376	0.163

5293 rows × 19 columns

In [24]:

```
test_data
```

Out[24]:

Date	Price	Vol	Change %	GDPC1_PCH	DFF	Price_USD	Change %_USD	UNRATE	INDPRO	T10YIE	Production_Oil	Volume_Lag
2023-11-29	0.501552	0.182008	0.782296	0.023942	0.985102	0.734689	0.529418	0.026316	0.939555	0.728188	0.95461	0.16192
2023-11-30	0.487507	0.315908	0.755875	0.023942	0.985102	0.751987	0.529621	0.026316	0.939555	0.734899	0.95461	0.18200
2023-12-01	0.473536	0.202805	0.755570	0.023942	0.985102	0.746611	0.529347	0.026316	0.922993	0.731544	1.00000	0.31590
2023-12-04	0.465923	0.219669	0.762267	0.023942	0.985102	0.756896	0.529538	0.026316	0.922993	0.728188	1.00000	0.20280
2023-12-05	0.460600	0.202646	0.764702	0.023942	0.985102	0.764843	0.529509	0.026316	0.922993	0.714765	1.00000	0.21966
2023-12-06	0.438868	0.246771	0.745952	0.023942	0.985102	0.767181	0.558824	0.026316	0.922993	0.704698	1.00000	0.20264
2023-12-07	0.438572	0.191516	0.770364	0.023942	0.985102	0.752922	0.529238	0.026316	0.922993	0.714765	1.00000	0.24677
2023-12-08	0.452543	0.170753	0.787349	0.023942	0.985102	0.763908	0.529544	0.026316	0.922993	0.728188	1.00000	0.19151
2023-12-11	0.453208	0.155024	0.771521	0.023942	0.985102	0.766012	0.529435	0.026316	0.922993	0.721477	1.00000	0.17075
2023-12-12	0.433176	0.183341	0.747595	0.023942	0.985102	0.760402	0.529347	0.026316	0.922993	0.711409	1.00000	0.15502
2023-12-13	0.439533	0.173437	0.778339	0.023942	0.985102	0.737260	0.529129	0.026316	0.922993	0.711409	1.00000	0.18334
2023-12-14	0.455130	0.155748	0.789237	0.023942	0.985102	0.715989	0.529150	0.026316	0.922993	0.731544	1.00000	0.17343
2023-12-15	0.454021	0.053950	0.769451	0.023942	0.985102	0.729780	0.529582	0.026316	0.922993	0.731544	1.00000	0.15574
2023-12-18	0.461709	0.041763	0.779618	0.023942	0.985102	0.730014	0.529415	0.026316	0.922993	0.728188	1.00000	0.05395
2023-12-19	0.468879	0.014503	0.778887	0.023942	0.985102	0.720898	0.529300	0.026316	0.922993	0.721477	1.00000	0.04176

Date	Price	Vol	Change %	GDPC1_PCH	DFF	Price_USD	Change %_USD	UNRATE	INDPRO	T10YIE	Production_Oil	Volume_Lag
2023-12-20	0.474645	0.154431	0.777183	0.023942	0.985102	0.726508	0.529482	0.026316	0.922993	0.721477	1.00000	0.01450
2023-12-21	0.472206	0.142352	0.768051	0.023942	0.985102	0.713184	0.529250	0.026316	0.922993	0.721477	1.00000	0.15443
2023-12-22	0.469766	0.125753	0.767990	0.023942	0.985102	0.709911	0.529371	0.026316	0.922993	0.721477	1.00000	0.14235
2023-12-25	0.471467	0.134431	0.772617	0.023942	0.985102	0.701613	0.529322	0.026316	0.922993	0.714765	1.00000	0.12575
2023-12-26	0.484624	0.117911	0.785401	0.023942	0.985102	0.704535	0.529341	0.026316	0.922993	0.718121	1.00000	0.13443
2023-12-27	0.473832	0.143109	0.758980	0.023942	0.985102	0.693315	0.529274	0.026316	0.922993	0.708054	1.00000	0.11791
2023-12-28	0.456535	0.148437	0.751492	0.023942	0.985102	0.698925	0.529482	0.026316	0.922993	0.711409	1.00000	0.14310
2023-12-29	0.455648	0.121171	0.769694	0.023942	0.985102	0.701262	0.558824	0.026316	0.922993	0.711409	1.00000	0.14843

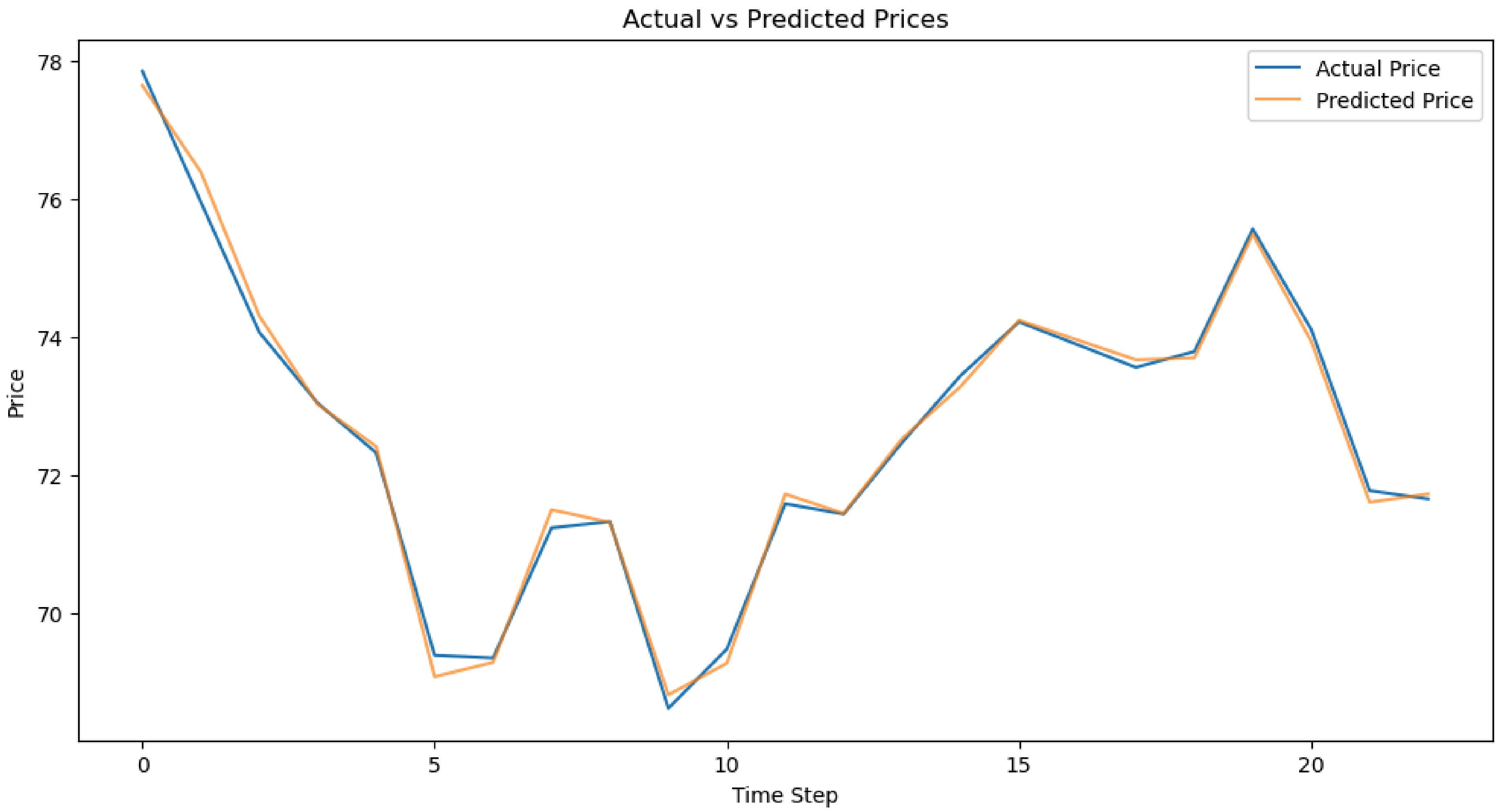
RANDOMFOREST

In [25]:
```
# Define the Random Forest model
model = RandomForestRegressor()

# Define the grid search parameters
param_grid = {
    'n_estimators': [50, 100, 150,200,300],
    'max_depth': [None, 10, 20,30,50],
    'min_samples_split': [2, 5, 10]
}
# param_grid = {
#     'n_estimators': [50, 100, 150, 200, 300],  # Increased the range of n_estimators
#     'max_depth': [None, 10, 20, 30, 50],        # Added more options for max_depth
#     'min_samples_split': [2, 5, 10, 15],        # Added an additional value
#     'min_samples_leaf': [1, 2, 4, 6],           # New parameter: minimum number of samples required at each leaf node
```

```
#     'max_features': ['auto', 'sqrt', 'log2'],  # New parameter: number of features to consider when looking for the
#     'bootstrap': [True, False],                # New parameter: whether bootstrap samples are used when building tre
#     'max_leaf_nodes': [None, 10, 50, 100, 200] # New parameter: maximum number of leaf nodes
# }

# Start the grid search timer
start_time = time.time()

# Perform grid search
grid = GridSearchCV(estimator=model, param_grid=param_grid, scoring='neg_mean_squared_error', cv=5)
grid_result = grid.fit(X_train, y_train)

#Calculate elapsed time
rf_elapsed_time = time.time() - start_time

# Output best parameters from grid search
print("Best Parameters:", grid_result.best_params_)
print("Grid Search Elapsed Time: {:.2f} seconds".format(rf_elapsed_time))

# Predict with the best model
best_rf_model = grid.best_estimator_
rf_predictions = best_rf_model.predict(X_test)

# Inverse transform predictions and actual values
rf_predictions = target_scaler.inverse_transform(rf_predictions.reshape(-1, 1))
actual = target_scaler.inverse_transform(y_test.values.reshape(-1, 1))

# Calculate evaluation metrics
rf_mse = mean_squared_error(actual, rf_predictions)
rf_rmse = np.sqrt(rf_mse)
rf_r2 = r2_score(actual, rf_predictions)

# Output metrics
print("Mean Squared Error:", rf_mse)
print("Root Mean Squared Error:", rf_rmse)
print("R^2 Score:", rf_r2)
```

```
Best Parameters: {'max_depth': 50, 'min_samples_split': 5, 'n_estimators': 100}
Grid Search Elapsed Time: 1824.17 seconds
Mean Squared Error: 0.030077014809935573
Root Mean Squared Error: 0.17342726086153692
R^2 Score: 0.9939353091001745
```

In [26]:
```
# Plot results
plt.figure(figsize=(12, 6))
plt.plot(actual, label='Actual Price')
plt.plot(rf_predictions, label='Predicted Price', alpha=0.7)
plt.title('Actual vs Predicted Prices')
plt.xlabel('Time Step')
plt.ylabel('Price')
plt.legend()
plt.show()
```



In [28]:
```
# Define the trend for actual prices
actual_trend = ['Flat' if actual[i] == actual[i-1] else 'Up' if actual[i] > actual[i-1] else 'Down' for i in range(1,
actual_trend.insert(0, 'Flat')

# Define the trend for predicted prices
predicted_trend = ['Flat' if rf_predictions[i] == rf_predictions[i-1] else 'Up' if rf_predictions[i] > rf_predictions[
predicted_trend.insert(0, 'Flat')

# Create the DataFrame for price comparison
price_comparison_df = pd.DataFrame({
    'Actual Price': actual.flatten(),
    'Predicted Price': rf_predictions.flatten(),
    'Actual Trend': actual_trend,
    'Predicted Trend': predicted_trend
})

# Calculate the accuracy of trend prediction
correct_trends = sum(1 for actual, predicted in zip(actual_trend, predicted_trend) if actual == predicted)
total_trends = len(actual_trend)
rf_accuracy = correct_trends / total_trends

# Display the DataFrame
print(price_comparison_df)
print(f'Accuracy of correctly predicting the trend: {rf_accuracy:.2%}')
```

```
    Actual Price  Predicted Price Actual Trend Predicted Trend
0          77.86        77.652925         Flat            Flat
1          75.96        76.396907         Down            Down
2          74.07        74.307607         Down            Down
3          73.04        73.022559         Down            Down
4          72.32        72.412205         Down            Down
5          69.38        69.068775         Down            Down
6          69.34        69.276593         Down              Up
7          71.23        71.492428           Up              Up
8          71.32        71.310489           Up            Down
9          68.61        68.806471         Down            Down
10         69.47        69.264122           Up              Up
11         71.58        71.720620           Up              Up
12         71.43        71.438814         Down            Down
13         72.47        72.525711           Up              Up
14         73.44        73.281500           Up              Up
15         74.22        74.243157           Up              Up
16         73.89        73.957656         Down            Down
17         73.56        73.670857         Down            Down
18         73.79        73.698383           Up              Up
19         75.57        75.494487           Up              Up
20         74.11        73.939577         Down            Down
21         71.77        71.602363         Down            Down
22         71.65        71.722050         Down              Up
Accuracy of correctly predicting the trend: 86.96%
```

GRADIENT BOOSTING

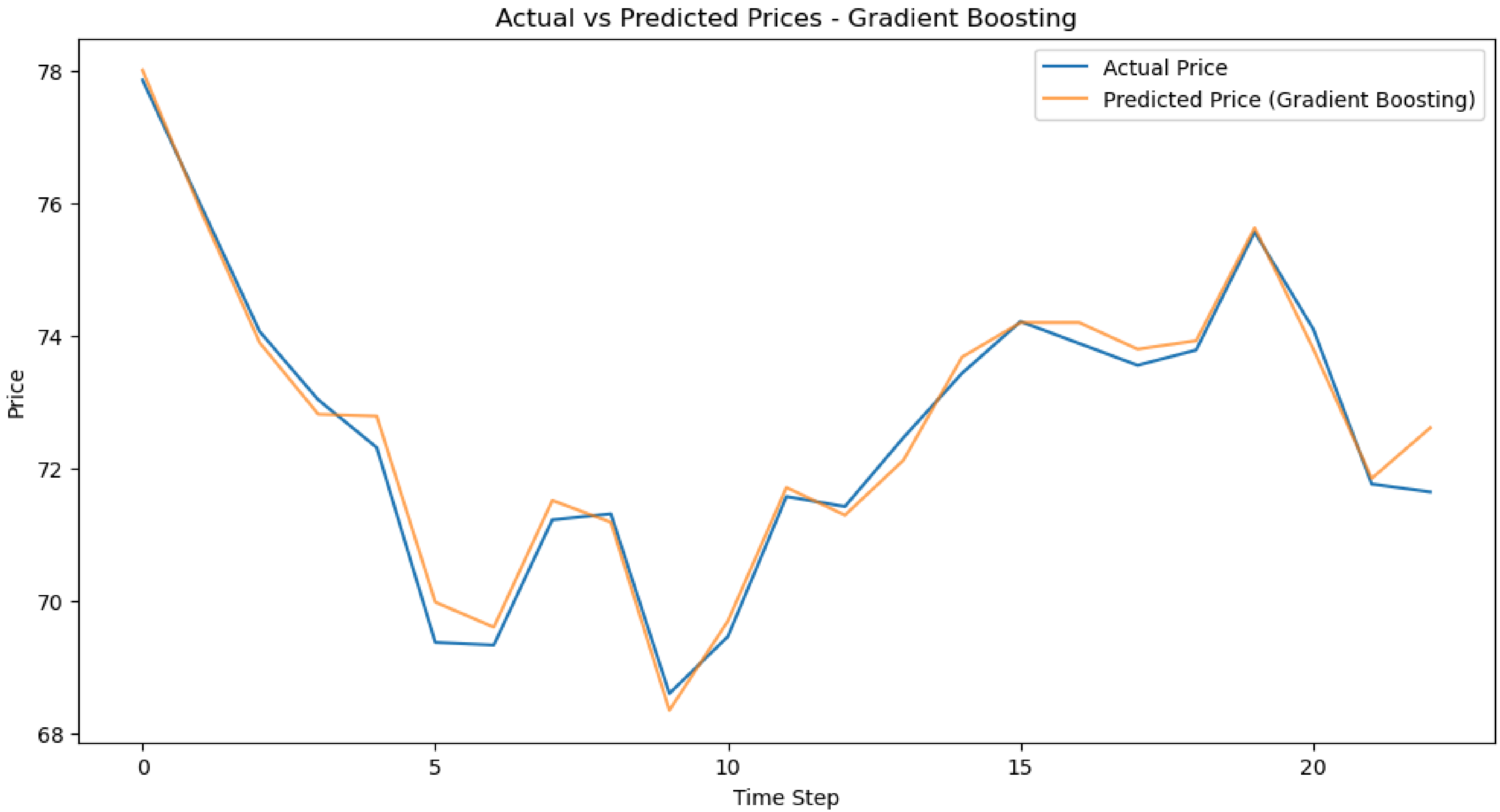
In [29]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import MinMaxScaler
import xgboost as xgb

# Gradient Boosting
gb_model = GradientBoostingRegressor()
gb_param_grid = {
    'n_estimators': [50, 100, 150,200,250],
    'learning_rate': [0.01, 0.1,0.2, 0.5],
    'max_depth': [3, 5, 7,10]
```

```
}
# gb_param_grid = {
#     'n_estimators': [50, 100, 150, 200, 250],      # Expanded range of n_estimators
#     'learning_rate': [0.01, 0.05, 0.1, 0.2, 0.5],  # More granular options for learning rate
#     'max_depth': [3, 5, 7, 9, 11],                 # Added more options for max_depth
#     'subsample': [0.5, 0.7, 0.9, 1.0],             # New parameter: fraction of samples used for fitting the indivi
#     'min_samples_split': [2, 5, 10, 20],           # New parameter: minimum number of samples required to split an i
#     'min_samples_leaf': [1, 2, 4, 6],              # New parameter: minimum number of samples required to be at a le
#     'max_features': ['sqrt', 'log2', None],        # New parameter: the number of features to consider when looking
# }

# Start the grid search timer
start_time = time.time()

gb_grid = GridSearchCV(estimator=gb_model, param_grid=gb_param_grid, scoring='neg_mean_squared_error', cv=5)
gb_grid_result = gb_grid.fit(X_train, y_train)

#Calculate elapsed time
gb_elapsed_time = time.time() - start_time

# Output best parameters from grid search
print("Gradient Boosting - Best Parameters:", gb_grid_result.best_params_)
print("Grid Search Elapsed Time: {:.2f} seconds".format(gb_elapsed_time))


# Predict with the best Gradient Boosting model
best_gb_model = gb_grid.best_estimator_
gb_predictions = best_gb_model.predict(X_test)

# Inverse transform predictions and actual values for Gradient Boosting
gb_predictions = target_scaler.inverse_transform(gb_predictions.reshape(-1, 1))
actual = target_scaler.inverse_transform(y_test.values.reshape(-1, 1))

# Calculate evaluation metrics for Gradient Boosting
gb_mse = mean_squared_error(actual, gb_predictions)
gb_rmse = np.sqrt(gb_mse)
gb_r2 = r2_score(actual, gb_predictions)

# Output metrics for Gradient Boosting
print("Gradient Boosting - Mean Squared Error:", gb_mse)
print("Gradient Boosting - Root Mean Squared Error:", gb_rmse)
print("Gradient Boosting - R^2 Score:", gb_r2)
```

```
Gradient Boosting - Best Parameters: {'learning_rate': 0.5, 'max_depth': 3, 'n_estimators': 200}
Grid Search Elapsed Time: 3431.14 seconds
Gradient Boosting - Mean Squared Error: 0.10521046582511237
Gradient Boosting - Root Mean Squared Error: 0.3243616281638634
Gradient Boosting - R^2 Score: 0.9787854958782283
```

In [30]:

```
# Plot actual vs predicted for Gradient Boosting
plt.figure(figsize=(12, 6))
plt.plot(actual, label='Actual Price')
plt.plot(gb_predictions, label='Predicted Price (Gradient Boosting)', alpha=0.7)
plt.title('Actual vs Predicted Prices - Gradient Boosting')
plt.xlabel('Time Step')
plt.ylabel('Price')
plt.legend()
plt.show()
```



In [31]:

```
# Define the trend for actual prices
actual_trend_gb = ['Flat' if actual[i] == actual[i-1] else 'Up' if actual[i] > actual[i-1] else 'Down' for i in range(
actual_trend_gb.insert(0, 'Flat')

# Define the trend for predicted prices
predicted_trend_gb = ['Flat' if gb_predictions[i] == gb_predictions[i-1] else 'Up' if gb_predictions[i] > gb_predictic
predicted_trend_gb.insert(0, 'Flat')

# Create the DataFrame for price comparison
price_comparison_df_gb = pd.DataFrame({
    'Actual Price': actual.flatten(),
```

```
    'Predicted Price': gb_predictions.flatten(),
    'Actual Trend': actual_trend_gb,
    'Predicted Trend': predicted_trend_gb
})

# Calculate the accuracy of trend prediction
correct_trends_gb = sum(1 for actual, predicted in zip(actual_trend_gb, predicted_trend_gb) if actual == predicted)
total_trends_gb = len(actual_trend_gb)
gb_accuracy = correct_trends_gb / total_trends_gb

# Display the DataFrame
print(price_comparison_df_gb)
print(f'Accuracy of correctly predicting the trend for Gradient Boosting: {gb_accuracy:.2%}')
```

```
    Actual Price  Predicted Price Actual Trend Predicted Trend
0          77.86        78.008903         Flat            Flat
1          75.96        75.877168         Down            Down
2          74.07        73.901305         Down            Down
3          73.04        72.822460         Down            Down
4          72.32        72.794054         Down            Down
5          69.38        69.988009         Down            Down
6          69.34        69.610422         Down            Down
7          71.23        71.521885           Up              Up
8          71.32        71.192767           Up            Down
9          68.61        68.356652         Down            Down
10         69.47        69.703311           Up              Up
11         71.58        71.717169           Up              Up
12         71.43        71.299521         Down            Down
13         72.47        72.128581           Up              Up
14         73.44        73.683797           Up              Up
15         74.22        74.204512           Up              Up
16         73.89        74.205133         Down              Up
17         73.56        73.803250         Down            Down
18         73.79        73.930458           Up              Up
19         75.57        75.635373           Up              Up
20         74.11        73.808968         Down            Down
21         71.77        71.854068         Down            Down
22         71.65        72.617078         Down              Up
Accuracy of correctly predicting the trend for Gradient Boosting: 86.96%
```

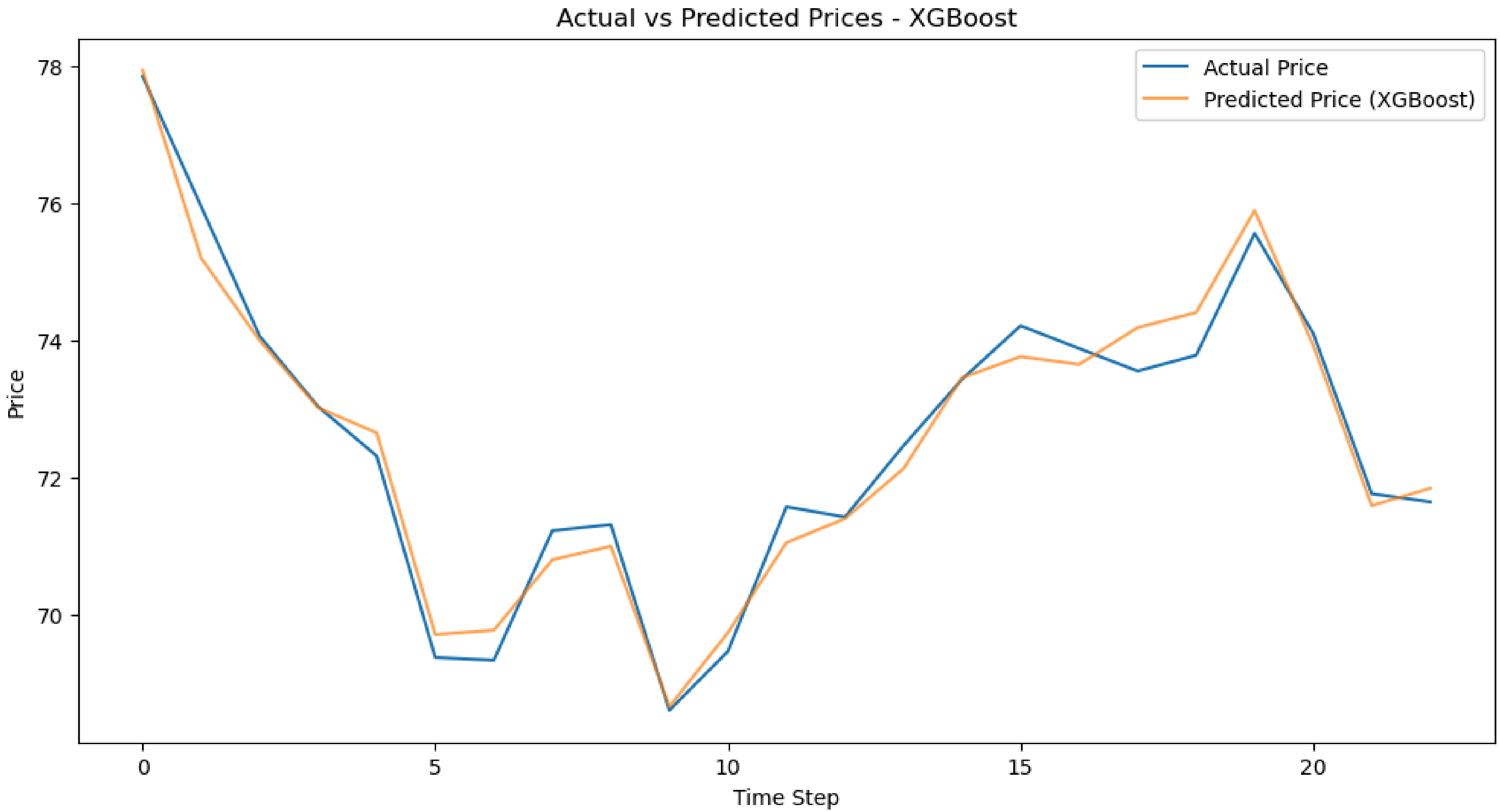
XGBOOSTING

In [32]:
```
##### XGBoost
xgb_model = xgb.XGBRegressor()

xgb_param_grid = {
    'n_estimators': [50, 100, 150,200],
    'learning_rate': [0.01, 0.1,0.2, 0.5],
    'max_depth': [3, 5, 7,10]
}

# Start the grid search timer
start_time = time.time()

xgb_grid = GridSearchCV(estimator=xgb_model, param_grid=xgb_param_grid, scoring='neg_mean_squared_error', cv=5)
xgb_grid_result = xgb_grid.fit(X_train, y_train)

#Calculate elapsed time
xgb_elapsed_time = time.time() - start_time

# Output best parameters from grid search
print("XGBoost - Best Parameters:", xgb_grid_result.best_params_)
print("Grid Search Elapsed Time: {:.2f} seconds".format(xgb_elapsed_time))

# Predict with the best XGBoost model
best_xgb_model = xgb_grid.best_estimator_
xgb_predictions = best_xgb_model.predict(X_test)

# Inverse transform predictions for XGBoost
xgb_predictions = target_scaler.inverse_transform(xgb_predictions.reshape(-1, 1))

# Calculate evaluation metrics for XGBoost
xgb_mse = mean_squared_error(actual, xgb_predictions)
xgb_rmse = np.sqrt(xgb_mse)
xgb_r2 = r2_score(actual, xgb_predictions)

# Output metrics for XGBoost
print("XGBoost - Mean Squared Error:", xgb_mse)
print("XGBoost - Root Mean Squared Error:", xgb_rmse)
print("XGBoost - R^2 Score:", xgb_r2)
```

```
XGBoost - Best Parameters: {'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 200}
Grid Search Elapsed Time: 60.12 seconds
XGBoost - Mean Squared Error: 0.1302556345376016
XGBoost - Root Mean Squared Error: 0.36090945476338193
XGBoost - R^2 Score: 0.9737354200068339
```

In [33]:

```
# Plot actual vs predicted for XGBoost
plt.figure(figsize=(12, 6))
plt.plot(actual, label='Actual Price')
plt.plot(xgb_predictions, label='Predicted Price (XGBoost)', alpha=0.7)
plt.title('Actual vs Predicted Prices - XGBoost')
plt.xlabel('Time Step')
plt.ylabel('Price')
plt.legend()
plt.show()
```



In [34]:

```
# Define the trend for predicted prices
predicted_trend_xgb = ['Flat' if xgb_predictions[i] == xgb_predictions[i-1] else 'Up' if xgb_predictions[i] > xgb_prec
predicted_trend_xgb.insert(0, 'Flat')

# Create the DataFrame for price comparison
price_comparison_df_xgb = pd.DataFrame({
    'Actual Price': actual.flatten(),
    'Predicted Price': xgb_predictions.flatten(),
    'Actual Trend': actual_trend_gb,
    'Predicted Trend': predicted_trend_xgb
})
```

```
# Calculate the accuracy of trend prediction
correct_trends_xgb = sum(1 for actual, predicted in zip(actual_trend_gb, predicted_trend_xgb) if actual == predicted)
total_trends_xgb = len(actual_trend_gb)
xgb_accuracy = correct_trends_xgb / total_trends_xgb

# Display the DataFrame
print(price_comparison_df_xgb)
print(f'Accuracy of correctly predicting the trend for XGBoost: {xgb_accuracy:.2%}')
```

```
    Actual Price  Predicted Price Actual Trend Predicted Trend
0          77.86        77.947792         Flat            Flat
1          75.96        75.209335         Down            Down
2          74.07        74.005341         Down            Down
3          73.04        73.025772         Down            Down
4          72.32        72.658279         Down            Down
5          69.38        69.714790         Down            Down
6          69.34        69.778061         Down              Up
7          71.23        70.805969           Up              Up
8          71.32        71.003296           Up              Up
9          68.61        68.663574         Down            Down
10         69.47        69.742401           Up              Up
11         71.58        71.056801           Up              Up
12         71.43        71.406166         Down              Up
13         72.47        72.135368           Up              Up
14         73.44        73.462494           Up              Up
15         74.22        73.770615           Up              Up
16         73.89        73.657852         Down            Down
17         73.56        74.193260         Down              Up
18         73.79        74.414169           Up              Up
19         75.57        75.904282           Up              Up
20         74.11        73.935249         Down            Down
21         71.77        71.596977         Down            Down
22         71.65        71.848106         Down              Up
Accuracy of correctly predicting the trend for XGBoost: 82.61%
```

LINEAR

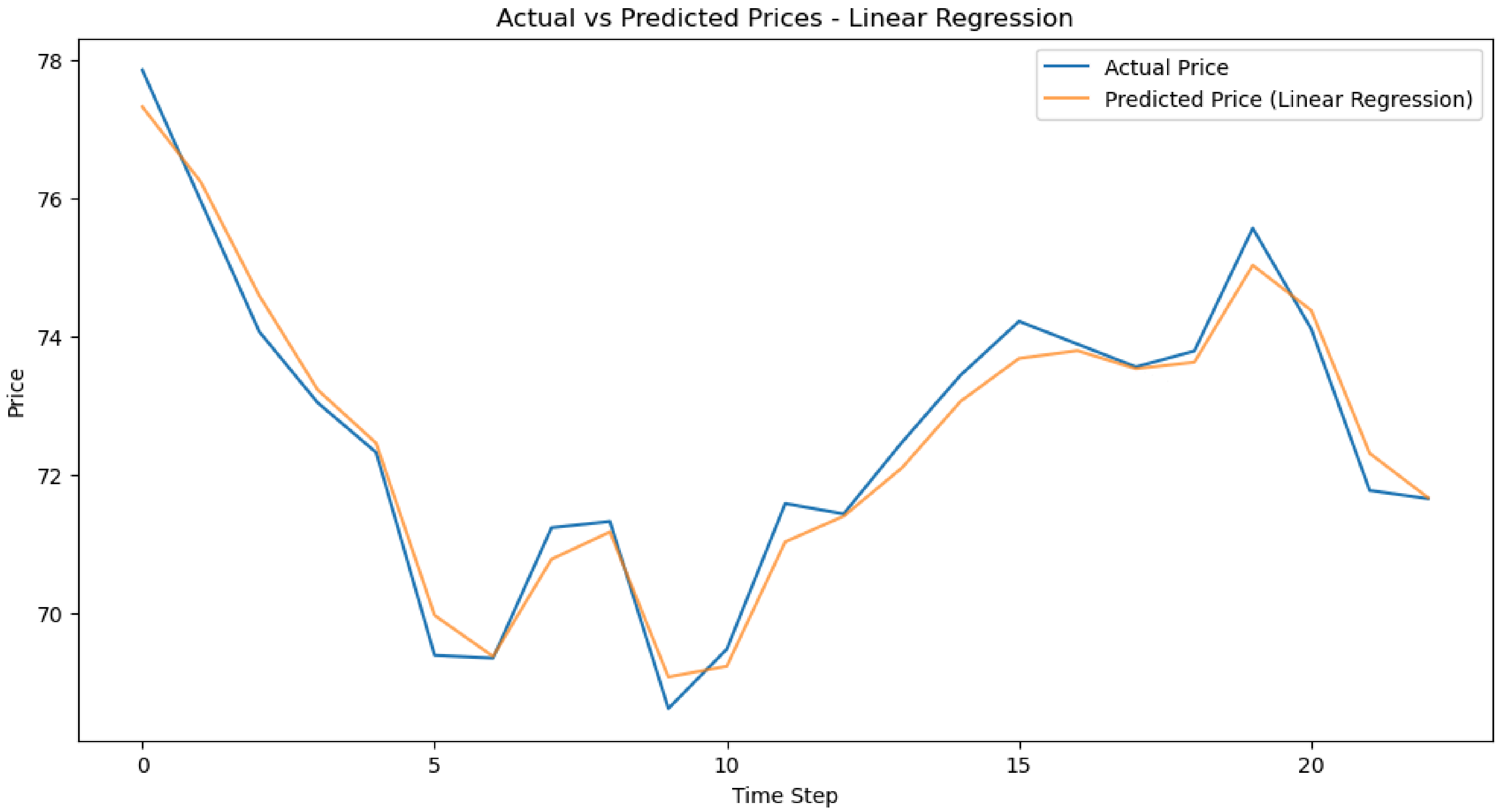
In [35]:
```
import time
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import numpy as np
```

```
# Initialize the Linear Regression model
lr_model = LinearRegression()

# Start timing
start_time = time.time()

# Train the Linear Regression model
lr_model.fit(X_train, y_train)

# End timing for training
training_time = time.time() - start_time

# Predict with the Linear Regression model
lr_predictions = lr_model.predict(X_test)

# Inverse transform predictions for Linear Regression, if required
lr_predictions = target_scaler.inverse_transform(lr_predictions.reshape(-1, 1))

# Calculate evaluation metrics for Linear Regression
lr_mse = mean_squared_error(actual, lr_predictions)
lr_rmse = np.sqrt(lr_mse)
lr_r2 = r2_score(actual, lr_predictions)

# Output metrics for Linear Regression
print("Linear Regression - Mean Squared Error:", lr_mse)
print("Linear Regression - Root Mean Squared Error:", lr_rmse)
print("Linear Regression - R^2 Score:", lr_r2)
print("Training Time (Linear Regression):", training_time, "seconds")
```

```
Linear Regression - Mean Squared Error: 0.1342515887981157
Linear Regression - Root Mean Squared Error: 0.36640358731611194
Linear Regression - R^2 Score: 0.9729296808870109
Training Time (Linear Regression): 0.010608911514282227 seconds
```

In [36]:

```
# Plot actual vs predicted for Linear Regression
plt.figure(figsize=(12, 6))
plt.plot(actual, label='Actual Price')
plt.plot(lr_predictions, label='Predicted Price (Linear Regression)', alpha=0.7)
plt.title('Actual vs Predicted Prices - Linear Regression')
plt.xlabel('Time Step')
plt.ylabel('Price')
plt.legend()
plt.show()
```



In [37]:
```
# Define the trend for predicted prices
predicted_trend_lr = ['Flat' if lr_predictions[i] == lr_predictions[i-1] else 'Up' if lr_predictions[i] > lr_predictic
predicted_trend_lr.insert(0, 'Flat')

# Create the DataFrame for price comparison
price_comparison_df_lr = pd.DataFrame({
    'Actual Price': actual.flatten(),
    'Predicted Price': lr_predictions.flatten(),
    'Actual Trend': actual_trend_gb,
    'Predicted Trend': predicted_trend_lr
})
```

```
# Calculate the accuracy of trend prediction
correct_trends_lr = sum(1 for actual, predicted in zip(actual_trend_gb, predicted_trend_lr) if actual == predicted)
total_trends_lr = len(actual_trend_gb)
lr_accuracy = correct_trends_lr / total_trends_lr

# Display the DataFrame
print(price_comparison_df_lr)
print(f'Accuracy of correctly predicting the trend for Linear Regression: {lr_accuracy:.2%}')
```

```
    Actual Price  Predicted Price Actual Trend Predicted Trend
0          77.86        77.328052         Flat            Flat
1          75.96        76.237927         Down            Down
2          74.07        74.592997         Down            Down
3          73.04        73.226959         Down            Down
4          72.32        72.454594         Down            Down
5          69.38        69.959530         Down            Down
6          69.34        69.364705         Down            Down
7          71.23        70.772944           Up              Up
8          71.32        71.168787           Up              Up
9          68.61        69.066371         Down            Down
10         69.47        69.223135           Up              Up
11         71.58        71.025787           Up              Up
12         71.43        71.396598         Down              Up
13         72.47        72.099283           Up              Up
14         73.44        73.061040           Up              Up
15         74.22        73.682664           Up              Up
16         73.89        73.794763         Down              Up
17         73.56        73.533977         Down            Down
18         73.79        73.627606           Up              Up
19         75.57        75.033018           Up              Up
20         74.11        74.378502         Down            Down
21         71.77        72.307346         Down            Down
22         71.65        71.663688         Down            Down
Accuracy of correctly predicting the trend for Linear Regression: 91.30%
```

LSTM

In [38]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
import numpy as np
```

```
import matplotlib.pyplot as plt
import time
import pandas as pd

# Reshape input data for LSTM (samples, time steps, features)
X_lstm = np.concatenate((X_train.values, X_test.values))
X_lstm = X_lstm.reshape((X_lstm.shape[0], 1, X_lstm.shape[1]))
y_lstm = np.concatenate((y_train.values, y_test.values))

# Split the data
X_train_lstm, X_val_lstm, y_train_lstm, y_val_lstm = train_test_split(X_lstm, y_lstm, test_size=0.2, random_state=42)

# Define the LSTM model
def create_lstm_model(units=50, learning_rate=0.01):
    model = Sequential([
        LSTM(units, input_shape=(1, X_train.shape[1])),
        Dense(1)
    ])
    model.compile(optimizer=Adam(learning_rate=learning_rate), loss='mse')
    return model

# Define the parameter grid
lstm_param_grid = {
    'units': [50, 100, 150],
    'learning_rate': [0.01, 0.1, 0.001]
}

# Perform manual grid search
best_mse = float('inf')
best_params = {}
start_time = time.time()

for units in lstm_param_grid['units']:
    for lr in lstm_param_grid['learning_rate']:
        model = create_lstm_model(units=units, learning_rate=lr)
        history = model.fit(X_train_lstm, y_train_lstm, epochs=100, batch_size=32, validation_data=(X_val_lstm, y_val_
        mse = history.history['val_loss'][-1]
        if mse < best_mse:
            best_mse = mse
            best_params = {'units': units, 'learning_rate': lr}

lstm_elapsed_time = time.time() - start_time

print("LSTM - Best Parameters:", best_params)
```

```
print("Grid Search Elapsed Time: {:.2f} seconds".format(lstm_elapsed_time))

# Train the best model
best_model = create_lstm_model(units=best_params['units'], learning_rate=best_params['learning_rate'])
best_model.fit(X_lstm, y_lstm, epochs=100, batch_size=64, verbose=0)
```

```
LSTM - Best Parameters: {'units': 150, 'learning_rate': 0.001}
Grid Search Elapsed Time: 112.94 seconds
```

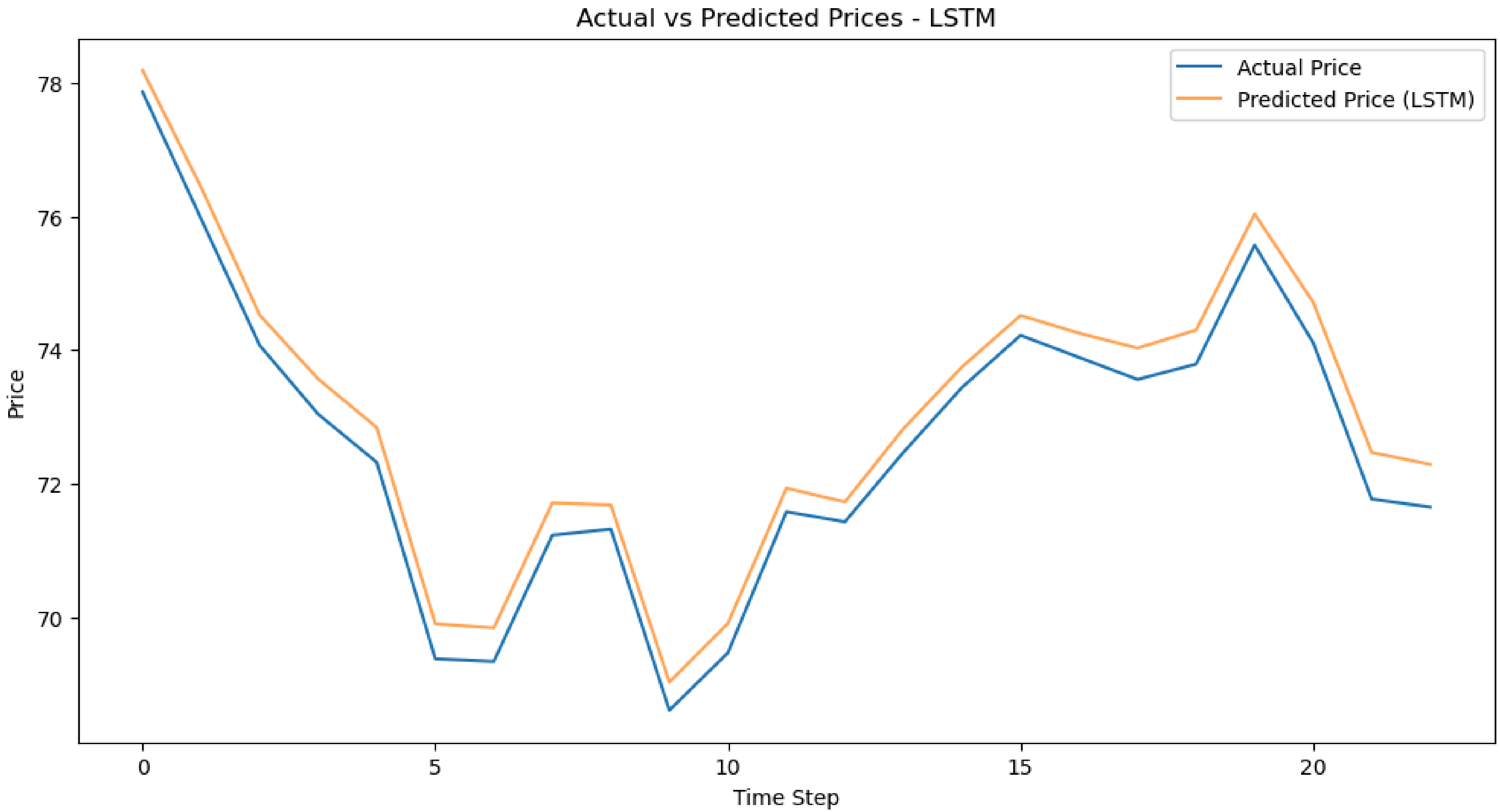
Out[38]:
```
<keras.src.callbacks.history.History at 0x2b025c490>
```

In [39]:
```
# Predict with the best LSTM model
lstm_predictions = best_model.predict(X_test.values.reshape((X_test.shape[0], 1, X_test.shape[1])))

# Inverse transform predictions and actual values for LSTM
lstm_predictions = target_scaler.inverse_transform(lstm_predictions)
actual = target_scaler.inverse_transform(y_test.values.reshape(-1, 1))

# Calculate evaluation metrics for LSTM
lstm_mse = mean_squared_error(actual, lstm_predictions)
lstm_rmse = np.sqrt(lstm_mse)
lstm_r2 = r2_score(actual, lstm_predictions)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
```

In [40]:
```
# Output metrics for LSTM
print("LSTM - Mean Squared Error:", lstm_mse)
print("LSTM - Root Mean Squared Error:", lstm_rmse)
print("LSTM - R^2 Score:", lstm_r2)

# Plot actual vs predicted for LSTM
plt.figure(figsize=(12, 6))
plt.plot(actual, label='Actual Price')
plt.plot(lstm_predictions, label='Predicted Price (LSTM)', alpha=0.7)
plt.title('Actual vs Predicted Prices - LSTM')
plt.xlabel('Time Step')
plt.ylabel('Price')
plt.legend()
plt.show()
```

```
LSTM - Mean Squared Error: 0.21539580321274351
LSTM - Root Mean Squared Error: 0.4641075341046981
LSTM - R^2 Score: 0.9565678650005712
```



In [41]:
```
# Define the actual trend
actual_trend = ['Flat' if actual[i] == actual[i-1] else 'Up' if actual[i] > actual[i-1] else 'Down' for i in range(1,
actual_trend.insert(0, 'Flat')

# Define the trend for predicted prices
predicted_trend_lstm = ['Flat' if lstm_predictions[i] == lstm_predictions[i-1] else 'Up' if lstm_predictions[i] > lstm
predicted_trend_lstm.insert(0, 'Flat')

# Create the DataFrame for price comparison
price_comparison_df_lstm = pd.DataFrame({
    'Actual Price': actual.flatten(),
```

```
    'Predicted Price': lstm_predictions.flatten(),
    'Actual Trend': actual_trend,
    'Predicted Trend': predicted_trend_lstm
})

# Calculate the accuracy of trend prediction
correct_trends_lstm = sum(1 for actual, predicted in zip(actual_trend, predicted_trend_lstm) if actual == predicted)
total_trends_lstm = len(actual_trend)
lstm_accuracy = correct_trends_lstm / total_trends_lstm

# Display the DataFrame
print(price_comparison_df_lstm)
print(f'Accuracy of correctly predicting the trend for LSTM: {lstm_accuracy:.2%}')
```

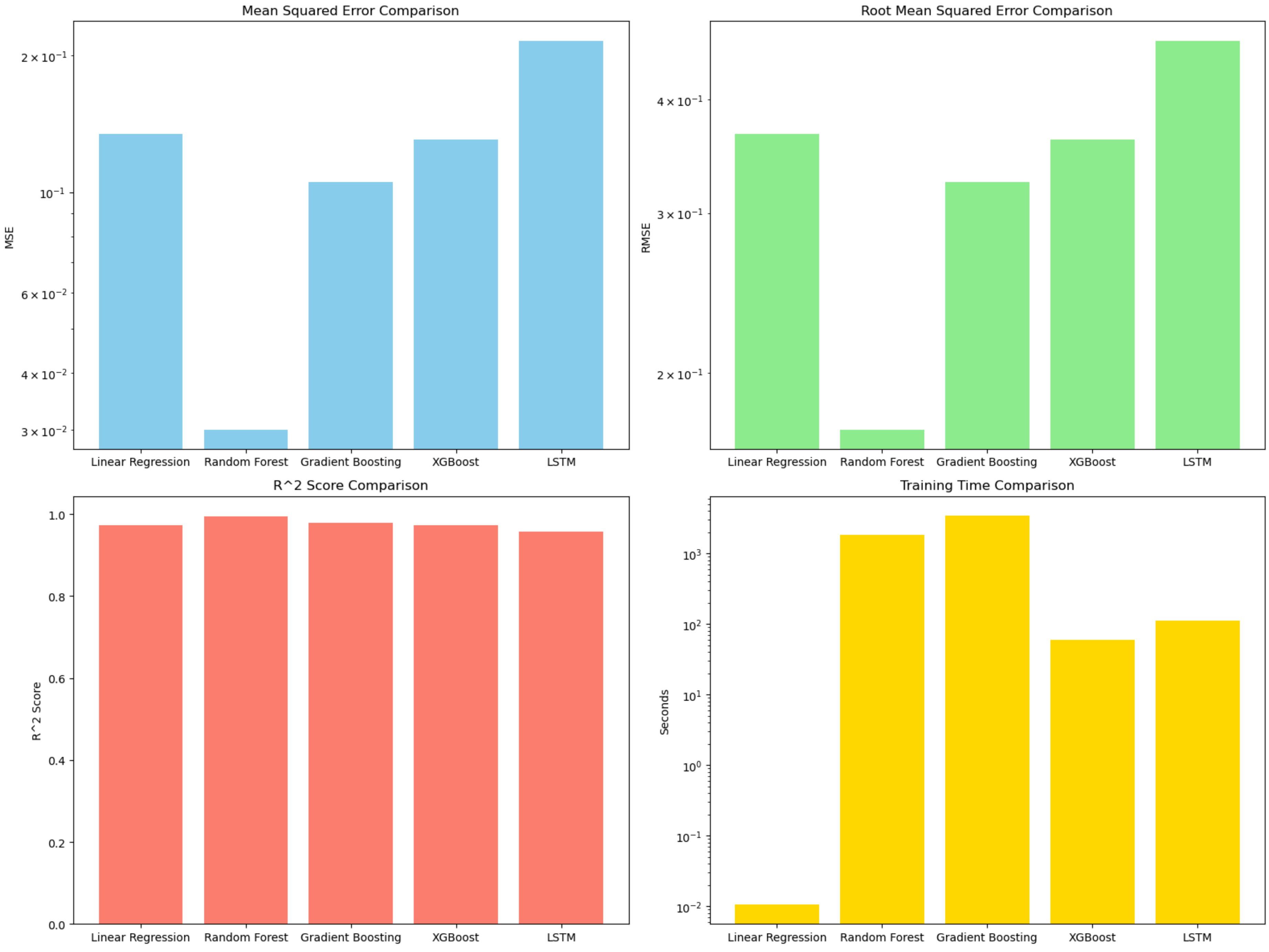
```
    Actual Price  Predicted Price Actual Trend Predicted Trend
0          77.86        78.185013         Flat            Flat
1          75.96        76.432503         Down            Down
2          74.07        74.523628         Down            Down
3          73.04        73.566536         Down            Down
4          72.32        72.841263         Down            Down
5          69.38        69.903671         Down            Down
6          69.34        69.842209         Down            Down
7          71.23        71.713249           Up              Up
8          71.32        71.681824           Up            Down
9          68.61        69.030746         Down            Down
10         69.47        69.909248           Up              Up
11         71.58        71.933151           Up              Up
12         71.43        71.727226         Down            Down
13         72.47        72.824158           Up              Up
14         73.44        73.747498           Up              Up
15         74.22        74.516914           Up              Up
16         73.89        74.252289         Down            Down
17         73.56        74.029228         Down            Down
18         73.79        74.298531           Up              Up
19         75.57        76.036003           Up              Up
20         74.11        74.714722         Down            Down
21         71.77        72.468010         Down            Down
22         71.65        72.289001         Down            Down
Accuracy of correctly predicting the trend for LSTM: 95.65%
```

COMPARISON

In [42]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# Metrics summary data
models = ['Linear Regression', 'Random Forest', 'Gradient Boosting', 'XGBoost', 'LSTM']
mse = [lr_mse, rf_mse, gb_mse, xgb_mse, lstm_mse]
rmse = [lr_rmse, rf_rmse, gb_rmse, xgb_rmse, lstm_rmse]
r2_scores = [lr_r2, rf_r2, gb_r2, xgb_r2, lstm_r2]
training_times = [training_time, rf_elapsed_time, gb_elapsed_time, xgb_elapsed_time, lstm_elapsed_time]
trend_accuracy = [lr_accuracy, rf_accuracy, gb_accuracy, xgb_accuracy, lstm_accuracy]

# Create a DataFrame to display the results neatly
results = pd.DataFrame({
    'Model': models,
    'MSE': mse,
    'RMSE': rmse,
    'R^2 Score': r2_scores,
    'Training Time (s)': training_times,
    'Trend Accuracy': trend_accuracy
})

# Display the results DataFrame
print(results)

# Plotting comparison
fig, axes = plt.subplots(2, 2, figsize=(16, 12))
axes = axes.flatten()

# MSE Comparison
axes[0].bar(models, mse, color='skyblue')
axes[0].set_title('Mean Squared Error Comparison')
axes[0].set_ylabel('MSE')
axes[0].set_yscale('log')

# RMSE Comparison
axes[1].bar(models, rmse, color='lightgreen')
axes[1].set_title('Root Mean Squared Error Comparison')
axes[1].set_ylabel('RMSE')
axes[1].set_yscale('log')

# R^2 Score Comparison
axes[2].bar(models, r2_scores, color='salmon')
```

```
axes[2].set_title('R^2 Score Comparison')
axes[2].set_ylabel('R^2 Score')

# Training Time Comparison
axes[3].bar(models, training_times, color='gold')
axes[3].set_title('Training Time Comparison')
axes[3].set_ylabel('Seconds')
axes[3].set_yscale('log')

plt.tight_layout()
plt.show()
```

```
               Model       MSE      RMSE  R^2 Score  Training Time (s)  \
0  Linear Regression  0.134252  0.366404   0.972930           0.010609
1      Random Forest  0.030077  0.173427   0.993935        1824.170488
2  Gradient Boosting  0.105210  0.324362   0.978785        3431.143399
3            XGBoost  0.130256  0.360909   0.973735          60.120689
4               LSTM  0.215396  0.464108   0.956568         112.942565

   Trend Accuracy
0        0.913043
1        0.869565
2        0.869565
3        0.826087
4        0.956522
```


Mean Squared Error Comparison
MSE
2×10^{-1}
10^{-1}
6×10^{-2}
4×10^{-2}
3×10^{-2}
Root Mean Squared Error Comparison
RMSE
4×10^{-1}
3×10^{-1}
2×10^{-1}
R^2 Score Comparison
R^2 Score
1.0
0.8
0.6
0.4
0.2
0.0
Training Time Comparison
Seconds
10^{3}
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
Linear Regression
Random Forest
Gradient Boosting
XGBoost
LSTM

TRAINING PERIODS DIFF

In [43]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
import xgboost as xgb
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Setup date offsets for various training periods
last_date = data_cleaned.index.max()
start_last_month = last_date - pd.DateOffset(months=1)
offsets = {
    '10_years': pd.DateOffset(years=10),
    '5_years': pd.DateOffset(years=5),
    '1_year': pd.DateOffset(years=1),
    '6_months': pd.DateOffset(months=6),
    '3_months': pd.DateOffset(months=3)
}

# Calculate the start dates for each training period
start_dates = {key: last_date - offset for key, offset in offsets.items()}

# Initialize models
models = {
    'RandomForest': best_rf_model,
    'GradientBoosting': best_gb_model,
    'XGBoost': best_xgb_model,
    'LinearRegression': LinearRegression(),
    'LSTM': best_model
}

# Prepare data containers
train_data = {}
test_data = data_cleaned[data_cleaned.index >= start_last_month]

# Split data
for key, start_date in start_dates.items():
    train_data[key] = data_cleaned[(data_cleaned.index >= start_date) & (data_cleaned.index < start_last_month)]

# Dictionary to store results
```

```
results = {model_name: {} for model_name in models}

# Training and testing each model for each time period
for model_name, model in models.items():
    for key, data in train_data.items():
        X_train = data[features]
        y_train = data[target].values.ravel()
        X_test = test_data[features]
        y_test = test_data[target]

        if model_name == 'LSTM':
            # Reshape input data for LSTM (samples, time steps, features)
            X_train_lstm = X_train.values.reshape((X_train.shape[0], 1, X_train.shape[1]))
            X_test_lstm = X_test.values.reshape((X_test.shape[0], 1, X_test.shape[1]))

            model.fit(X_train_lstm, y_train, epochs=100, batch_size=32, verbose=0)

            predictions = model.predict(X_test_lstm)
        else:
            model.fit(X_train, y_train)
            predictions = model.predict(X_test)

        predictions = target_scaler.inverse_transform(predictions.reshape(-1, 1))
        actual = target_scaler.inverse_transform(y_test.values.reshape(-1, 1))

        mse = mean_squared_error(actual, predictions)
        rmse = np.sqrt(mse)
        r2 = r2_score(actual, predictions)

        results[model_name][key] = {
            'MSE': mse,
            'RMSE': rmse,
            'R2': r2
        }
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
```

In [44]:

```
rows = []

# Loop through the dictionary to populate the rows list
```

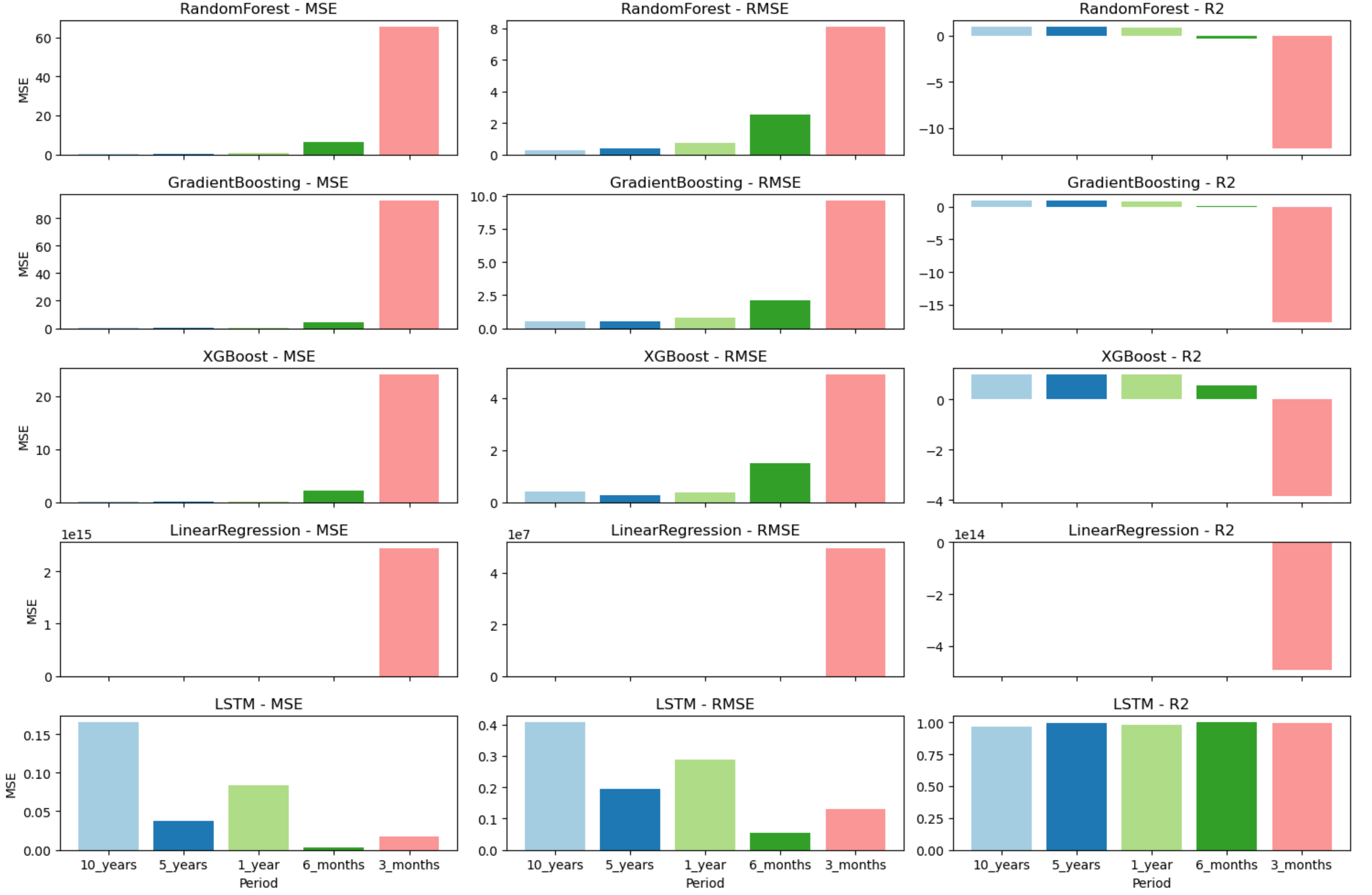
```
for model_name, periods in results.items():
    for period, metrics in periods.items():
        row = {
            'Model': model_name,
            'Period': period,
            'MSE': metrics['MSE'],
            'RMSE': metrics['RMSE'],
            'R2': metrics['R2']
        }
        rows.append(row)

# Create DataFrame
results_df = pd.DataFrame(rows)

# Setting multi-level index for better organization
results_df.set_index(['Model', 'Period'], inplace=True)

# Display the DataFrame
results_df
```

Out[44]:

Model	Period	MSE	RMSE	R2
RandomForest	10_years	7.281952e-02	2.698509e-01	9.853168e-01
	5_years	1.491649e-01	3.862187e-01	9.699226e-01
	1_year	5.671842e-01	7.531163e-01	8.856337e-01
	6_months	6.284685e+00	2.506927e+00	-2.672359e-01
	3_months	6.547136e+01	8.091438e+00	-1.220156e+01
GradientBoosting	10_years	2.455587e-01	4.955388e-01	9.504859e-01
	5_years	2.577297e-01	5.076709e-01	9.480317e-01
	1_year	6.146392e-01	7.839893e-01	8.760649e-01
	6_months	4.320361e+00	2.078548e+00	1.288479e-01
	3_months	9.254644e+01	9.620106e+00	-1.766095e+01
XGBoost	10_years	1.526854e-01	3.907498e-01	9.692127e-01
	5_years	7.511881e-02	2.740781e-01	9.848531e-01
	1_year	1.497058e-01	3.869183e-01	9.698135e-01
	6_months	2.247500e+00	1.499166e+00	5.468171e-01
	3_months	2.404776e+01	4.903851e+00	-3.848959e+00
LinearRegression	10_years	2.539240e-01	5.039088e-01	9.487991e-01
	5_years	2.711855e-01	5.207547e-01	9.453185e-01
	1_year	1.007057e-02	1.003522e-01	9.979694e-01
	6_months	6.178678e-02	2.485695e-01	9.875414e-01
	3_months	2.436330e+15	4.935920e+07	-4.912585e+14
LSTM	10_years	1.651818e-01	4.064256e-01	9.666930e-01
	5_years	3.794718e-02	1.948004e-01	9.923484e-01
	1_year	8.365632e-02	2.892340e-01	9.831316e-01
	6_months	3.082413e-03	5.551949e-02	9.993785e-01

		MSE	RMSE	R2
Model	**Period**			
	3_months	1.681489e-02	1.296723e-01	9.966095e-01

In [45]:
```
import matplotlib.pyplot as plt

# Setup plotting
metrics = ['MSE', 'RMSE', 'R2']
fig, axes = plt.subplots(nrows=len(models), ncols=len(metrics), figsize=(15, 10), sharex=True)

for row_idx, model in enumerate(models):
    for col_idx, metric in enumerate(metrics):
        ax = axes[row_idx][col_idx]
        periods = list(start_dates.keys())
        values = [results[model][period][metric] for period in periods]

        ax.bar(periods, values, color=plt.cm.Paired(np.arange(len(values))))
        ax.set_title(f'{model} - {metric}')
        if row_idx == len(models) - 1:
            ax.set_xlabel('Period')
        if col_idx == 0:
            ax.set_ylabel(metric)

plt.tight_layout()
plt.show()
```


RandomForest - MSE
RandomForest - RMSE
RandomForest - R2
GradientBoosting - MSE
GradientBoosting - RMSE
GradientBoosting - R2
XGBoost - MSE
XGBoost - RMSE
XGBoost - R2
LinearRegression - MSE
LinearRegression - RMSE
LinearRegression - R2
LSTM - MSE
LSTM - RMSE
LSTM - R2
MSE
1e15
1e7
1e14
10_years
5_years
1_year
6_months
3_months
Period

In [ ]:

In [ ]: