Modelling and Forecasting Brent Crude Oil with Auto Regressive Integrated Moving Average (ARIMA)

First things first make sure your google drive is linked to the notebook envirionment by running the cell below and allowing the necessary permissions.

In [ ]:
```
# from google.colab import drive
# drive.mount('/content/drive')
```

Importing Libraries: The first section of the code imports necessary libraries for data manipulation, visualization, and time series analysis.

In [ ]:
```
#%%
from math import sqrt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import pmdarima as pm
from pmdarima import auto_arima
from pmdarima.arima import ndiffs, nsdiffs
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tools.eval_measures import rmse
from math import sqrt
from sklearn.metrics import mean_squared_error,mean_absolute_error, mean_absolute_p
import warnings
warnings.filterwarnings("ignore")
```

Loading Data: The data is loaded from a pre processed CSV file into a pandas DataFrame. The index of the DataFrame is set to be the date.

In [ ]:
```
#%%

# Load data from csv file
data = pd.read_csv('Modified_Data.csv', index_col=[0], parse_dates=True)
data.head()
```

Out[ ]:

	Price
2002-01-01	19.96
2002-02-01	20.19
2002-03-01	24.03
2002-04-01	26.03
2002-05-01	25.69

The shape of the data shows the number of months and columns as (x,y)

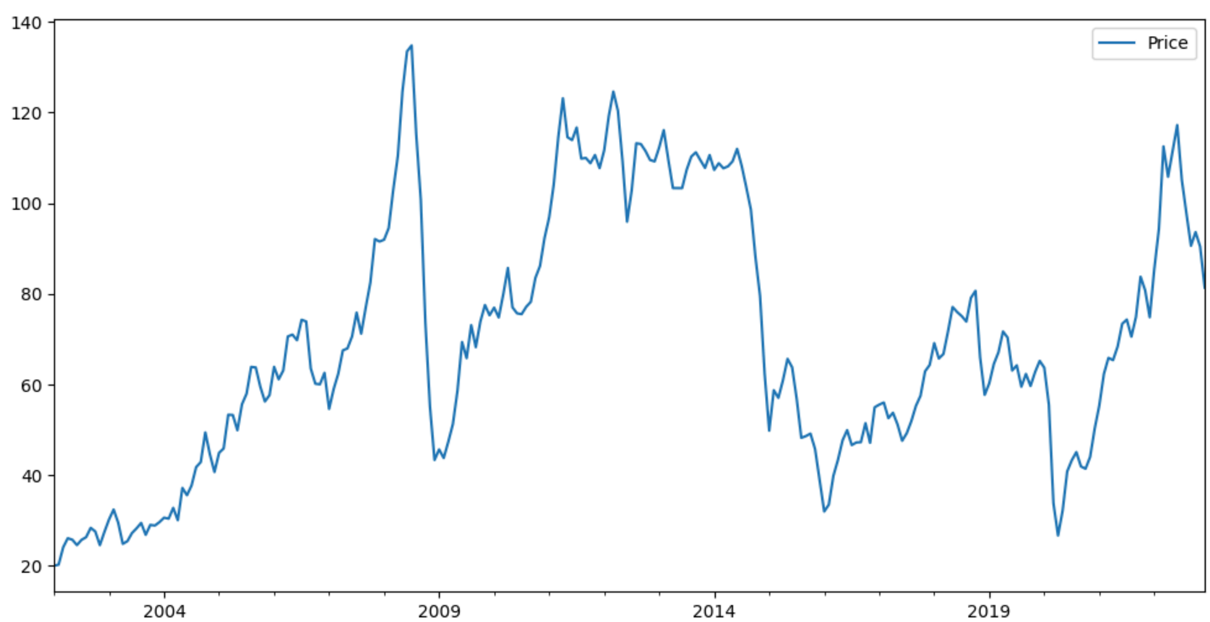
In [ ]:
```
data.shape
```

Out[ ]: (252, 1)

Plotting Data: The data is plotted using `Plotly`, a Python graphing library. This provides a visual representation of the time series data.

In [ ]:
```
#%%
# Plot data
# fig = px.line(data, x=data.index, y='Price', title='Brent Crude Oil Prices')
# fig.show()

# plot with matplotlib
data.plot(figsize=(12,6))
```

Out[ ]: <Axes: >



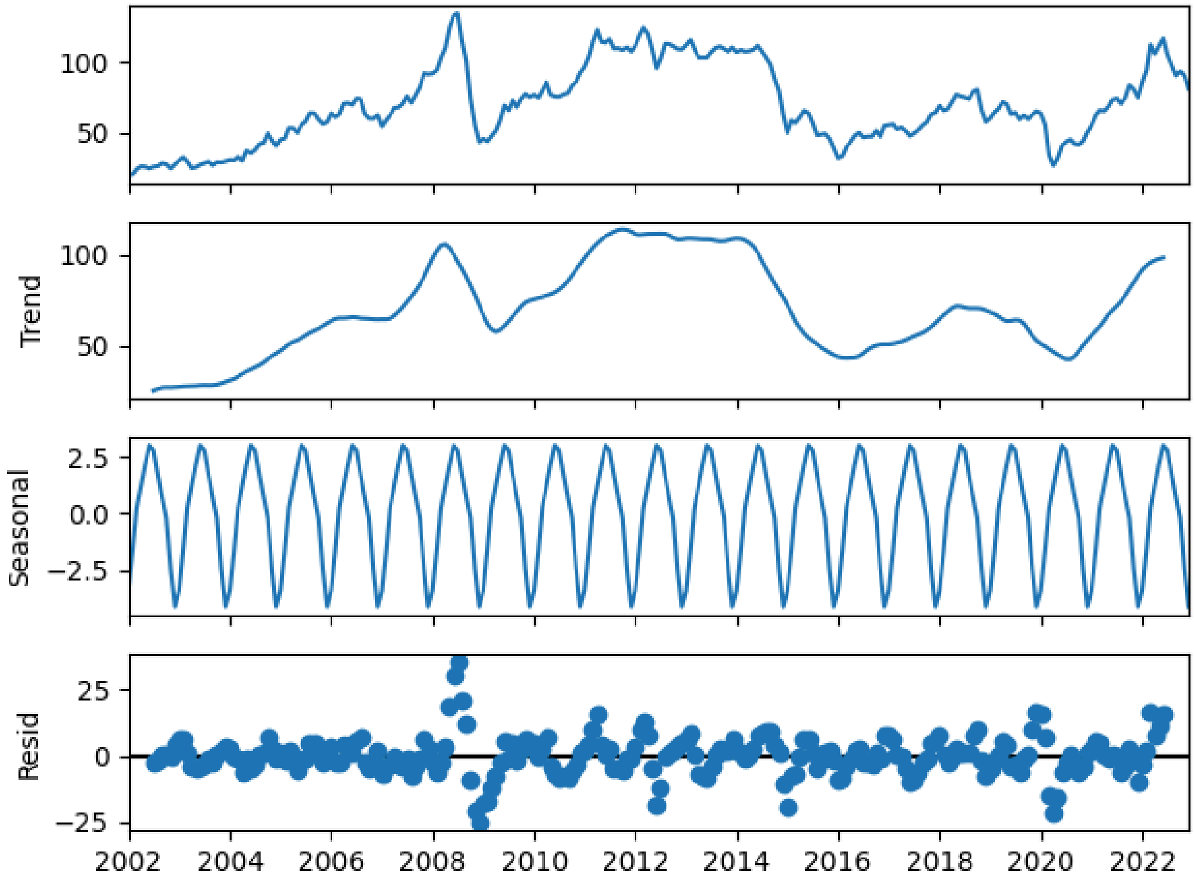
Checking Stationarity with Augmented Dickey-Fuller Test: The Augmented Dickey-Fuller test is used to check if the time series is stationary. A stationary time series' properties do not depend on the time at which the series is observed.

In [ ]:
```
#%%

def adf_test(data):
    result = adfuller(data)
    print('ADF Statistic: %f' % result[0])
    print('p-value: %f' % result[1])
    print('Number of lags used: %f' % result[2])
    if result[1] <= 0.05:
        print("Data is likely stationary.")
    else:
        print(f"Data may be non-stationary, consider differencing")

print("""Testing stationarity of data:""")
adf_test(data)
```

```
Testing stationarity of data:
ADF Statistic: -2.883602
p-value: 0.047288
Number of lags used: 1.000000
Data is likely stationary.
```

Decomposing Time Series: The time series is decomposed into trend, seasonal, and residual components.

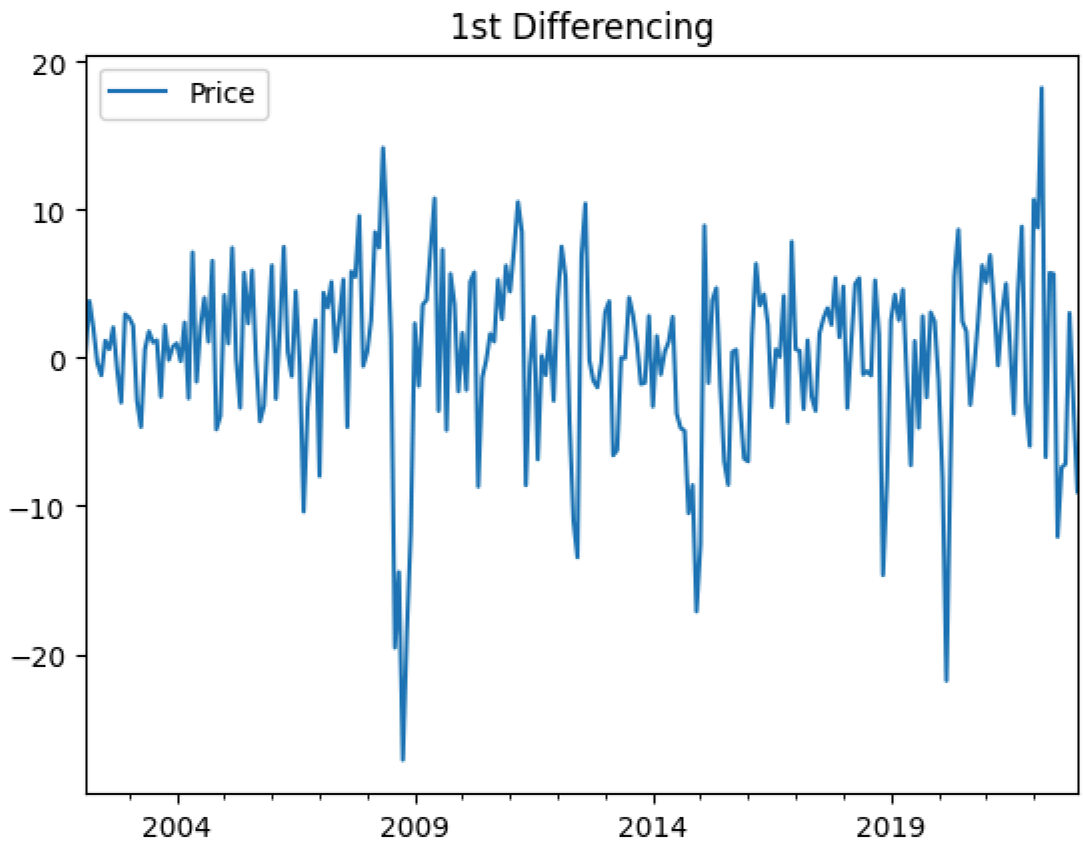
In [ ]:
```
#%%

# Decompose time series into trend, seasonal, and residual components
result = seasonal_decompose(data, model='additive')
result.plot()
plt.show()
```

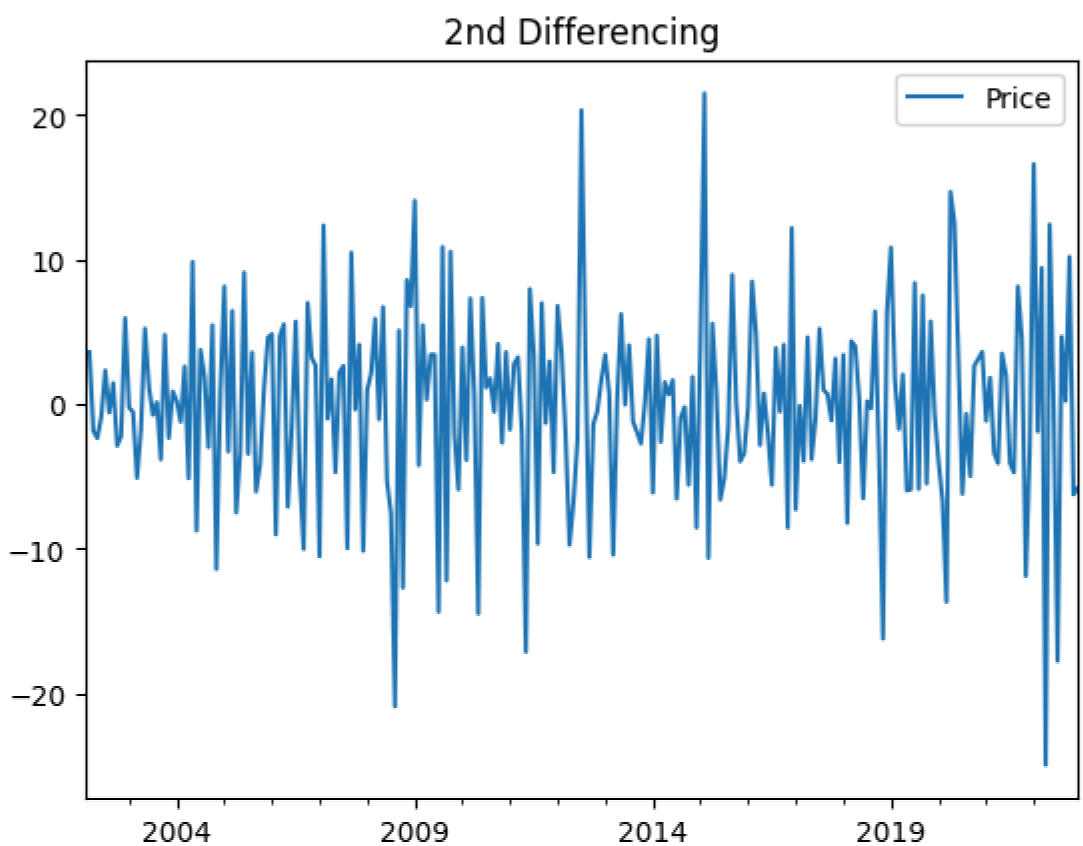


Differencing to Make the Series Stationary: If the series is not stationary, it is differenced. Differencing is the transformation of the series to make it stationary.

In [ ]:
```
#%%

# Differencing to make the series stationary and plot the differenced series
diff = data.diff()[1:] # [1:] to remove NaN value
diff_2 = diff.diff()

# plot and add legend in top right corner with plotly subplots
diff.plot(title="1st Differencing")
diff_2.plot(title="2nd Differencing")
```

Out[ ]:
```
<Axes: title={'center': '2nd Differencing'}>
```





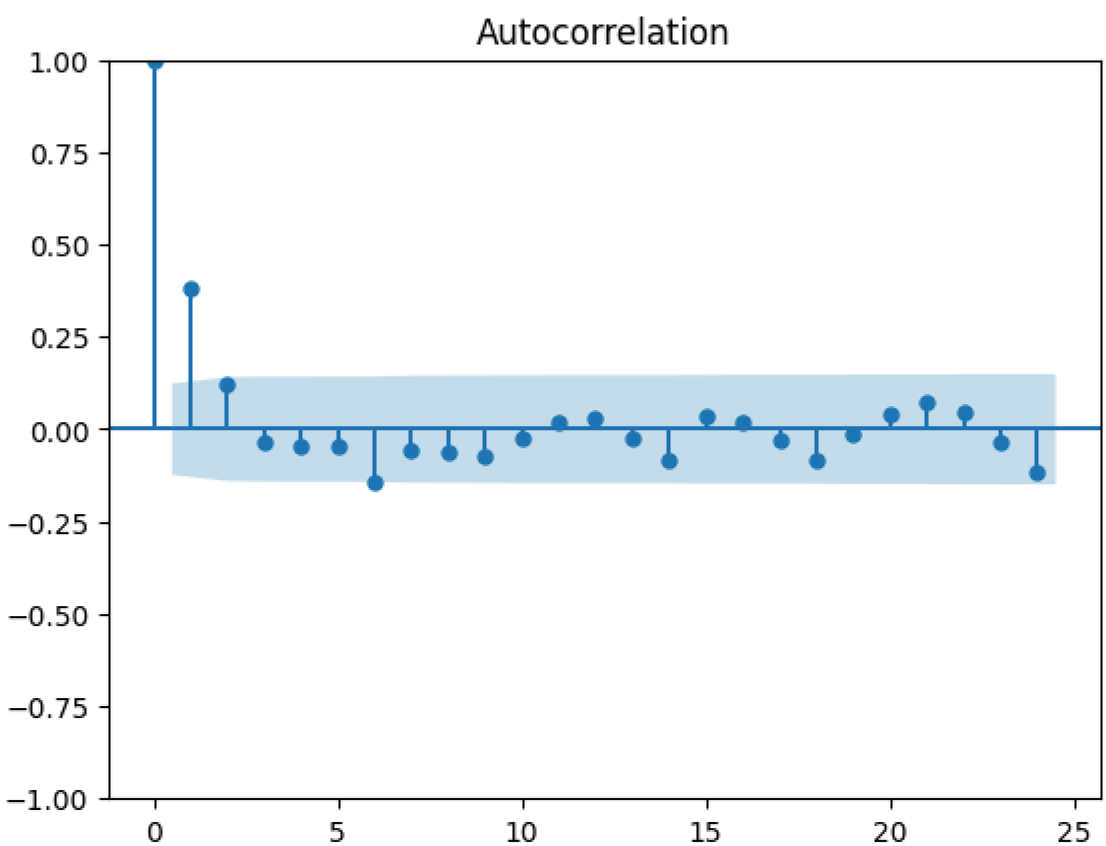
Determining the Order of Differencing: The ndiffs function is used to determine the minimum number of differencing needed to make the series stationary.

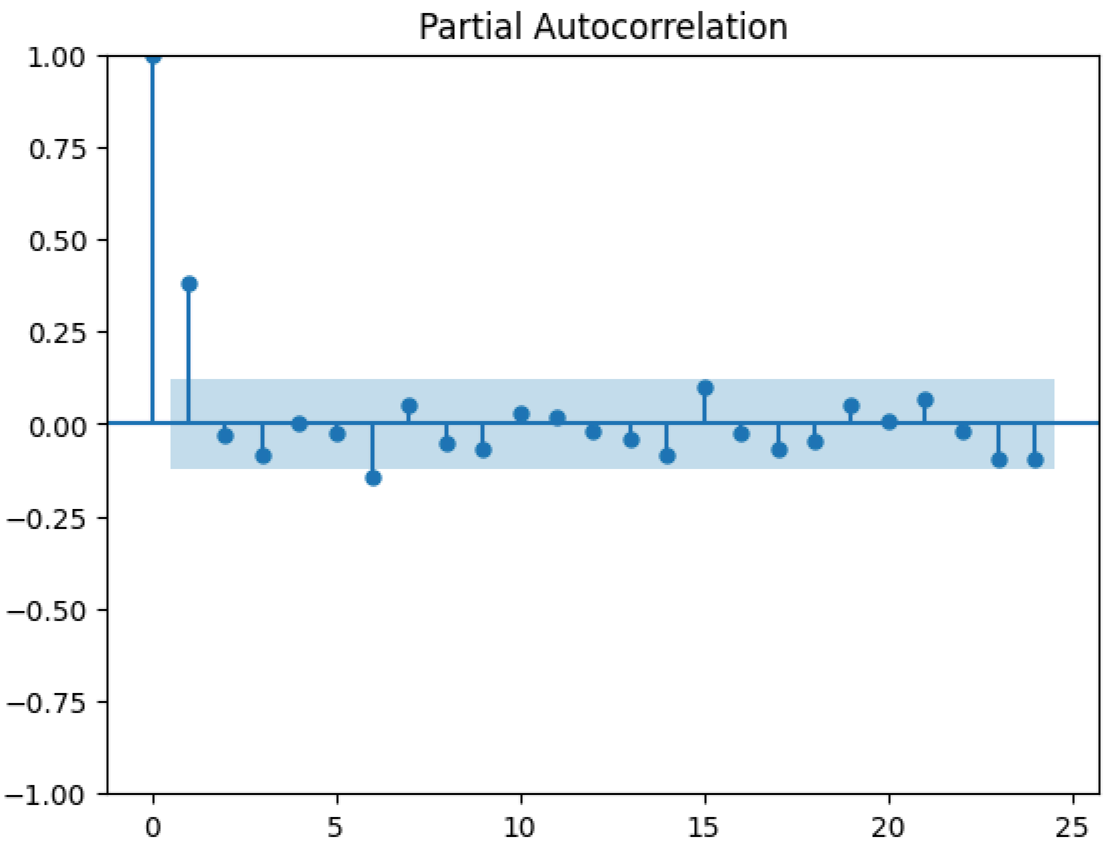
In [ ]:
```
#%%

# number of  differencing for stationary series with ndiffs

# Adf Test
print('ADF:', ndiffs(data, test='adf'))
# KPSS test
print('KPSS:', ndiffs(data, test='kpss'))
# PP test:
print('PP:', ndiffs(data, test='pp'))
```

```
ADF: 1
KPSS: 1
PP: 1
```

Determining the Order of the AR and MA terms: The Partial Autocorrelation Function `PACF` and the Autocorrelation Function `ACF` are plotted to determine the order of the `AR` and `MA` terms.

In [ ]:
```
#%%
# Find order of MA term Q
plot_acf(diff).show()
# Order of auto regressive term P
plot_pacf(diff).show()
```





Splitting Data into Train and Test Sets:

- The data is split into training and testing sets based on a specified date.
- The training set is used to train the model, and
- The testing set is used to evaluate the model's performance

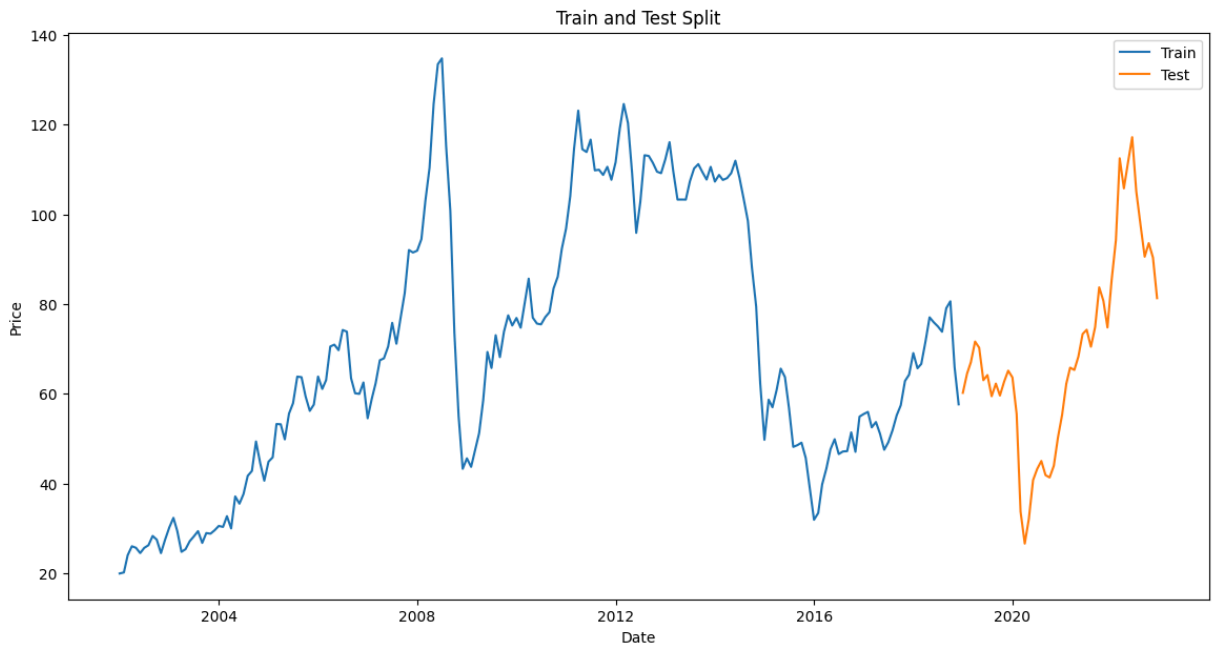
In [ ]:
```
#%%
# set the train and test data with start dates
train_start_date = '2002-01-01'
test_start_date = '2019-01-01'

# set the train and test data and print the dimensions of it
train = data.copy()[(data.index >= train_start_date) & (data.index < test_start_dat
test = data.copy()[data.index >= test_start_date][['Price']]

print('Training data shape: ', train.shape)
print('Test data shape: ', test.shape)
```

```
Training data shape:  (204, 1)
Test data shape:  (48, 1)
```

Plotting Train and Test Splits: The training and testing data are plotted to visualize the split.

In [ ]:
```
#%%

# Plot train and test splits
# fig = go.Figure()
```

```
# fig.add_trace(go.Scatter(x=train.index, y=train['Price'], mode='lines', name='Tra
# fig.add_trace(go.Scatter(x=test.index, y=test['Price'], mode='lines', name='Test'
# fig.update_layout(title='Train and Test Split', xaxis_title='Date', yaxis_title='
# fig.show()

plt.figure(figsize=(14, 7))
plt.plot(train.index, train['Price'], label='Train')
plt.plot(test.index, test['Price'], label='Test')
plt.title('Train and Test Split')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend(loc='best')
plt.show()
```



Model Selection with Auto ARIMA: The auto_arima function is used to automatically select the best `ARIMA` model based on the **Akaike Information Criterion** `AIC`.

In [ ]:
```
#%%

# use auto_arima to find best parameters
model = pm.auto_arima(data, seasonal=True, stepwise=True, suppress_warnings=True, t
print(f"ARIMA Order: {model.order}")
print(f"Seasonal Order: {model.seasonal_order}")
print(f"AIC: {model.aic()}")
print(f"BIC: {model.bic()}")
print(f"HQIC: {model.hqic()}")
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=1578.236, Time=0.34 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=1612.420, Time=0.02 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=1575.066, Time=0.04 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=1579.935, Time=0.07 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=1610.842, Time=0.03 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept   : AIC=1576.870, Time=0.12 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=1576.932, Time=0.09 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=1575.145, Time=0.41 sec
 ARIMA(1,1,0)(0,0,0)[0]             : AIC=1573.222, Time=0.04 sec
 ARIMA(2,1,0)(0,0,0)[0]             : AIC=1575.037, Time=0.07 sec
 ARIMA(1,1,1)(0,0,0)[0]             : AIC=1575.095, Time=0.04 sec
 ARIMA(0,1,1)(0,0,0)[0]             : AIC=1578.181, Time=0.04 sec
 ARIMA(2,1,1)(0,0,0)[0]             : AIC=1573.727, Time=0.17 sec

Best model:  ARIMA(1,1,0)(0,0,0)[0]
Total fit time: 1.515 seconds
ARIMA Order: (1, 1, 0)
Seasonal Order: (0, 0, 0, 0)
AIC: 1573.2220633964275
BIC: 1580.2729692746911
HQIC: 1576.0595242923355
```

Model Diagnostics: The residuals of the model are checked to ensure that the assumptions of the model are met.

In [ ]:

```
#%%
model.plot_diagnostics(figsize=(12, 8)).show()
model.summary()
```

Out[ ]:

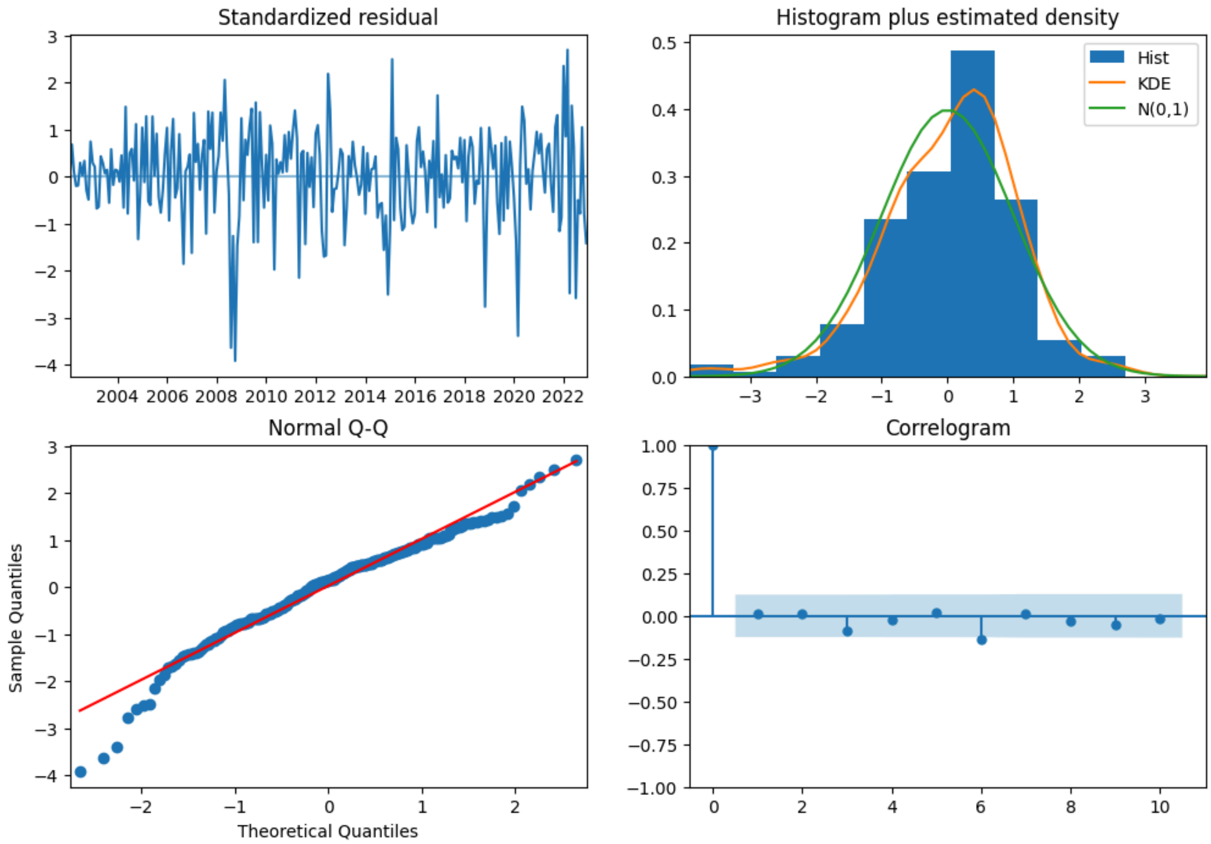
SARIMAX Results

Dep. Variable:	y	**No. Observations:**	252
Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-784.611
Date:	Fri, 17 May 2024	**AIC**	1573.222
Time:	14:20:17	**BIC**	1580.273
Sample:	01-01-2002	**HQIC**	1576.060
	- 12-01-2022		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.3831	0.043	8.923	0.000	0.299	0.467
sigma2	30.3674	2.072	14.656	0.000	26.306	34.429

Ljung-Box (L1) (Q):	0.03	**Jarque-Bera (JB):**	47.35
Prob(Q):	0.86	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.11	**Skew:**	-0.71
Prob(H) (two-sided):	0.62	**Kurtosis:**	4.59

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).



Model Fitting: The model is fitted to the training data.

In [ ]:
```
#%%
# Fit the model with the rraining set and best parameters found by auto_arima
model = SARIMAX(train, order= model.order)
model_fit = model.fit()
# residuals = model_fit.resid

# Print the summary of the model
model_fit.summary(alpha=0.05)
model_fit.summary(alpha=0.10)
```

Out[ ]:

SARIMAX Results

Dep. Variable:	Price	**No. Observations:**	204
Model:	SARIMAX(1, 1, 0)	**Log Likelihood**	-624.444
Date:	Fri, 17 May 2024	**AIC**	1252.888
Time:	14:20:19	**BIC**	1259.514
Sample:	01-01-2002	**HQIC**	1255.568
	- 12-01-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.05	0.95]
ar.L1	0.4152	0.047	8.894	0.000	0.338	0.492
sigma2	27.4768	2.023	13.585	0.000	24.150	30.804

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	45.36
Prob(Q):	0.95	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.38	**Skew:**	-0.74
Prob(H) (two-sided):	0.19	**Kurtosis:**	4.78

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Model Prediction: The model is used to make predictions on the test data.

In [ ]:

```
test.head()
```

Out[ ]:

	Price
2019-01-01	60.23
2019-02-01	64.50
2019-03-01	67.05
2019-04-01	71.66
2019-05-01	70.30

In [ ]:

```
# dynamic=False means that forecasts at each point are generated using the full his
predictions = model_fit.predict(start=test.index[0], end=test.index[-1], dynamic=Fa
residuals = test['Price'] - predictions
```

In [ ]:

```
predictions.tail()
```

Out[ ]:
```
2022-08-01    51.783188
2022-09-01    51.783188
2022-10-01    51.783188
2022-11-01    51.783188
2022-12-01    51.783188
Freq: MS, Name: predicted_mean, dtype: float64
```

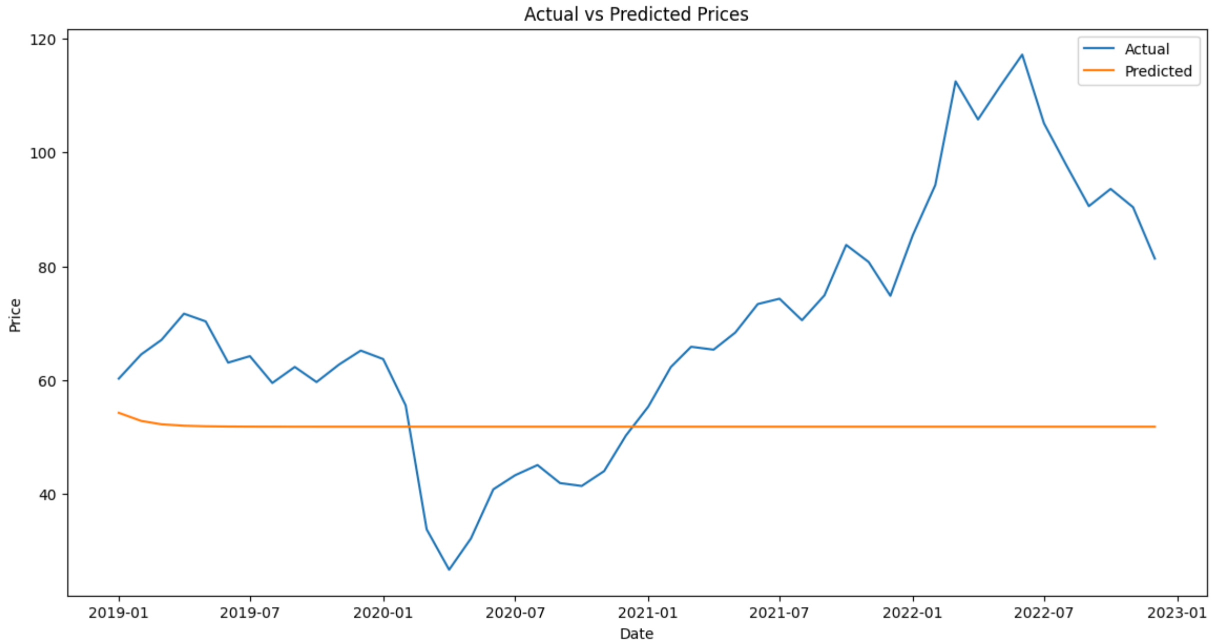
Model Evaluation: The model's performance is evaluated using the **Root Mean Squared Error** `RMSE`, **Mean Absolute Error** `MAE`, and **Mean Absolute Percentage Error** `MAPE`.

In [ ]:
```
#%%

# Calculate evaluation metrics
print(""" Error Metrics """)

mse = mean_squared_error(test, predictions)
rmse = sqrt(mse)
mae = mean_absolute_error(test, predictions)
mape = mean_absolute_percentage_error(test, predictions)
directional_accuracy = np.mean(np.sign(test['Price'].diff().dropna()) == np.sign(pr


print(f'Mean Squared Error: {mse:.3f}')
print(f'Mean Absolute Error: {mae:.3f}')
print(f'Root Mean Squared Error: {rmse:.3f}')
print(f'Mean Absolute Percentage Error: {mape*100:.3f}%')
print(f'Directional Accuracy: {directional_accuracy*100:.3f}%')
```

```
 Error Metrics
Mean Squared Error: 769.664
Mean Absolute Error: 22.322
Root Mean Squared Error: 27.743
Mean Absolute Percentage Error: 30.476%
Directional Accuracy: 31.915%
```

Plotting Actual vs Predicted Prices: The actual and predicted prices are plotted.

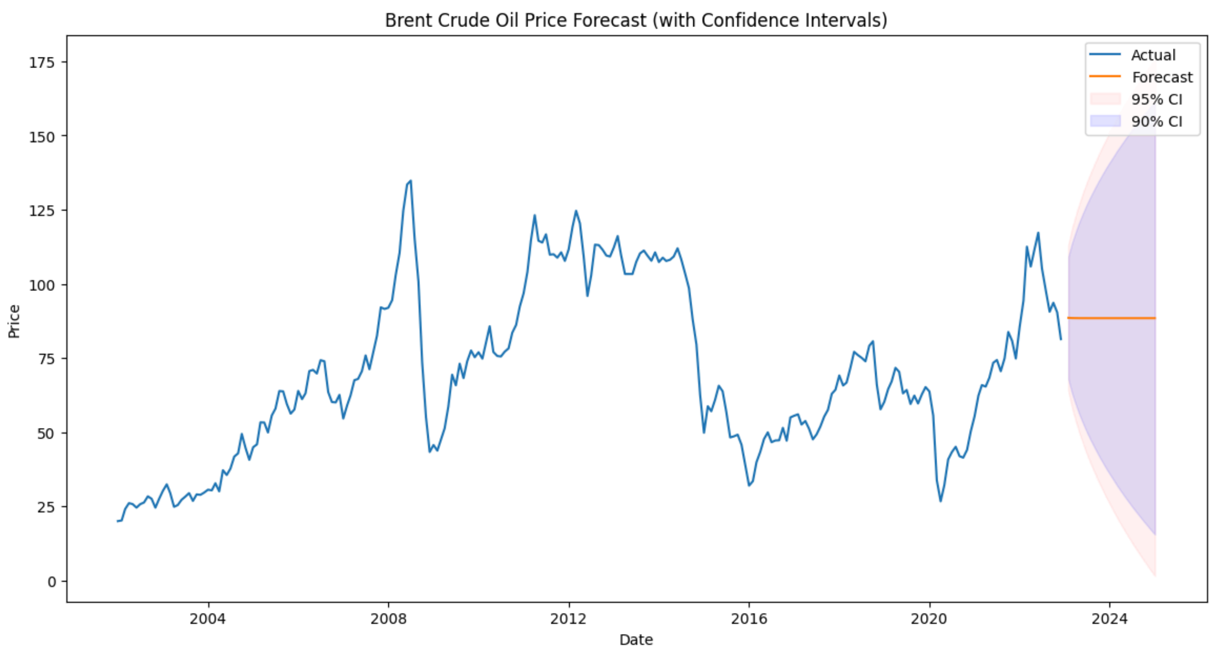
In [ ]:
```
fig = go.Figure()
fig.add_trace(go.Scatter(x=test.index, y=test['Price'], mode='lines', name='Actual'
fig.add_trace(go.Scatter(x=test.index, y=predictions, mode='lines', name='Predicted
fig.update_layout(title='Actual vs Predicted Prices', xaxis_title='Date', yaxis_tit
fig.show()


# plot with matplotlib
# import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
plt.plot(test.index, test['Price'], label='Actual')
plt.plot(test.index, predictions, label='Predicted')
plt.title('Actual vs Predicted Prices')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend(loc='best')
plt.show()
```



Forecasting Future Prices: The model is used to forecast future prices.

In [ ]:
```
# Forecasting with confidence intervals for the next 24 months

future_dates = pd.date_range(start='2023-01-01', periods=24, freq='M')

# Forecast with 95% confidence interval
forecast_obj_95 = model_fit.get_prediction(start=future_dates[0], end=future_dates[
forecast_95 = forecast_obj_95.predicted_mean
conf_int_95 = forecast_obj_95.conf_int(alpha=0.05)

# Forecast with 90% confidence interval
forecast_obj_90 = model_fit.get_prediction(start=future_dates[0], end=future_dates[
conf_int_90 = forecast_obj_90.conf_int(alpha=0.10)

# Plot the forecast with confidence intervals
fig = go.Figure()
fig.add_trace(go.Scatter(x=data.index, y=data['Price'], mode='lines', name='Actual'
fig.add_trace(go.Scatter(x=future_dates, y=forecast_95, mode='lines', name='Forecas
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_95.iloc[:, 0], mode='lines', na
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_95.iloc[:, 1], mode='lines', na
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_90.iloc[:, 0], mode='lines', na
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_90.iloc[:, 1], mode='lines', na
fig.update_layout(title='Brent Crude Oil Price Forecast (with Confidence Intervals)
fig.show()

# matplotlib plot

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

# Plot actual data
plt.plot(data.index, data['Price'], label='Actual')

# Plot forecast
plt.plot(future_dates, forecast_95, label='Forecast')
```

```
# Plot 95% confidence interval
plt.fill_between(future_dates, conf_int_95.iloc[:, 0], conf_int_95.iloc[:, 1], colo

# Plot 90% confidence interval
plt.fill_between(future_dates, conf_int_90.iloc[:, 0], conf_int_90.iloc[:, 1], colo

plt.title('Brent Crude Oil Price Forecast (with Confidence Intervals)')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend(loc='best')

# Format x-axis to display dates clearly
# plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
# plt.gca().xaxis.set_major_locator(mdates.DayLocator(interval=100))  # adjust inte
# plt.gcf().autofmt_xdate()

plt.show()
```



Applying a rolling window forecast

In [ ]:

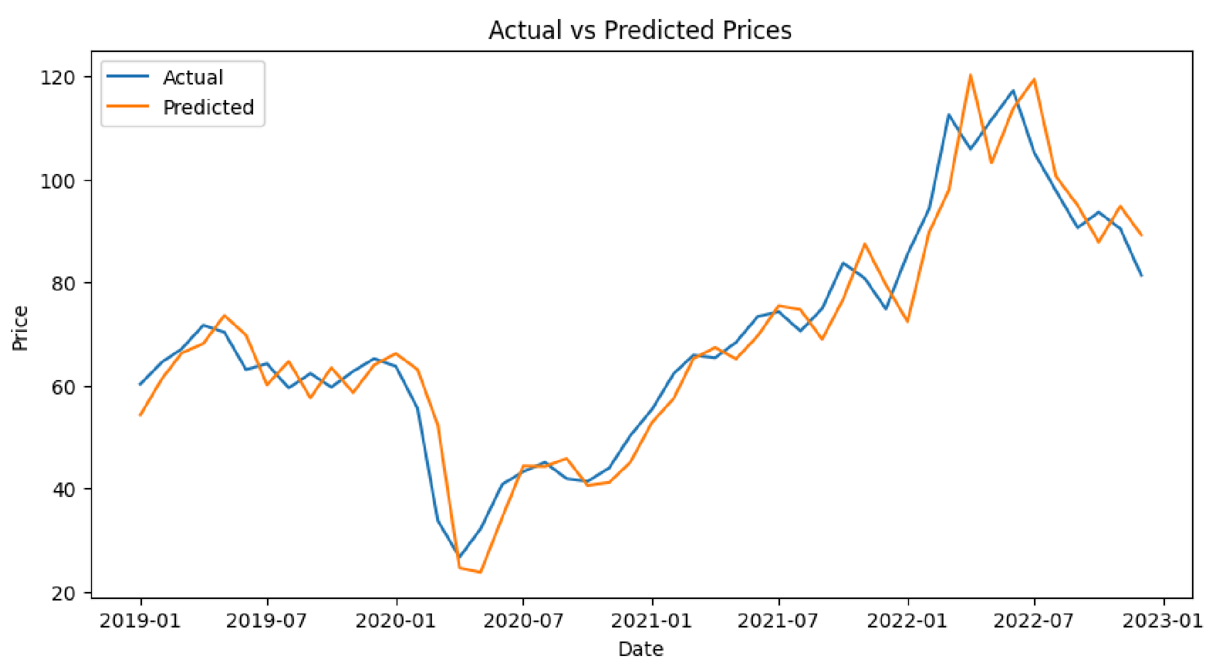
```
# use rolling window to forecast the next 24 months
window_size = 24 # 24 months
forecast = [] # to store the forecasted values
for i in range(len(test)):
    train_window = train.append(test.iloc[:i]) # add the test data to the training
    model = SARIMAX(train_window, order=model.order) # create the model
    model_fit = model.fit() # fit the model
    forecast.append(model_fit.forecast(steps=1)[0]) # forecast the next month

# Calculate evaluation metrics
mae = mean_absolute_error(test, forecast)
mse = mean_squared_error(test, forecast)
rmse = sqrt(mse)
mape = mean_absolute_percentage_error(test, forecast)
```

```
directional_accuracy = np.mean(np.sign(test.diff().dropna().values) == np.sign(np.d

# directional accuracy
```

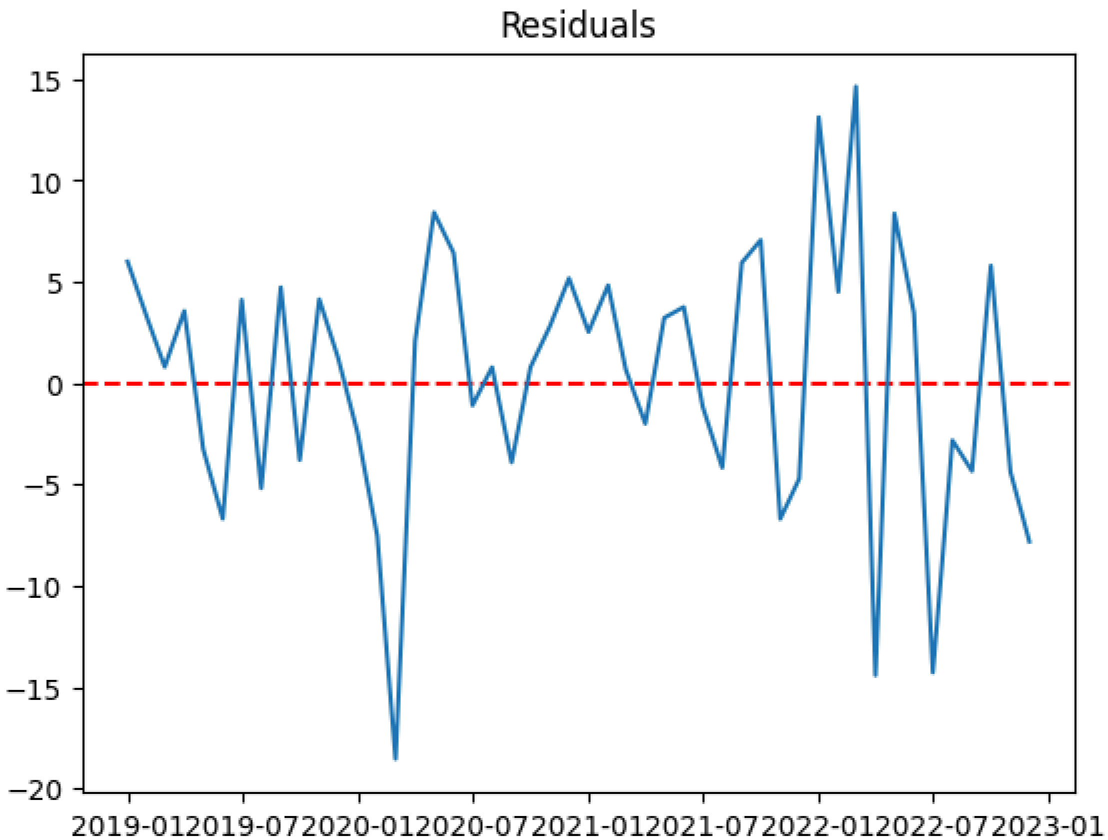
In [ ]:
```
print(f'Mean Squared Error: {mse:.3f}')
print(f'Root Mean Squared Error: {rmse:.3f}')
print(f'Mean Absolute Error: {mae:.3f}')
print(f'Mean Absolute Percentage Error: {mape*100:.3f}%')
print(f'Directional Accuracy: {directional_accuracy*100:.3f}%')
```

```
Mean Squared Error: 42.961
Root Mean Squared Error: 6.554
Mean Absolute Error: 5.241
Mean Absolute Percentage Error: 8.175%
Directional Accuracy: 51.109%
```

In [ ]:
```
# plot the actual and forecasted values
fig = go.Figure()
fig.add_trace(go.Scatter(x=test.index, y=test['Price'], mode='lines', name='Actual'
fig.add_trace(go.Scatter(x=test.index, y=forecast, mode='lines', name='Forecast'))
fig.update_layout(title='Actual vs Forecasted Prices', xaxis_title='Date', yaxis_ti
fig.show()


# plot with matplotlib
# import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
plt.plot(test.index, test['Price'], label='Actual')
plt.plot(test.index, forecast, label='Predicted')
plt.title('Actual vs Predicted Prices')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend(loc='best')
plt.show()
```



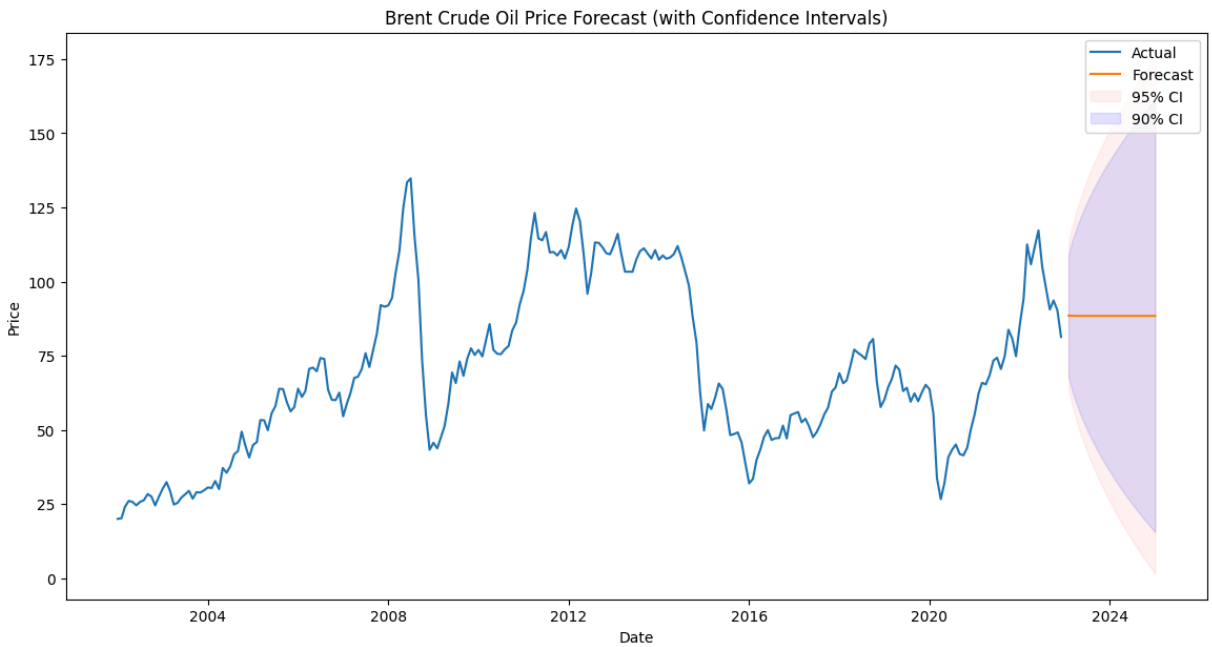
In [ ]:
```
# plot the residuals
residuals = test['Price'] - forecast
plt.axhline(y=0, color='red', linestyle='--')
plt.plot(residuals)
plt.title('Residuals')
plt.show()
```



In [ ]:
```
# Forecast with confidence intervals for the next 24 months
future_dates = pd.date_range(start='2023-01-01', periods=24, freq='M')

# Forecast with 95% confidence interval
forecast_obj_95 = model_fit.get_prediction(start=future_dates[0], end=future_dates[
forecast_95 = forecast_obj_95.predicted_mean
conf_int_95 = forecast_obj_95.conf_int(alpha=0.05)

# Forecast with 90% confidence interval
forecast_obj_90 = model_fit.get_prediction(start=future_dates[0], end=future_dates[
forecast_90 = forecast_obj_90.predicted_mean
conf_int_90 = forecast_obj_90.conf_int(alpha=0.10)

# Plot the forecast with confidence intervals
fig = go.Figure()
fig.add_trace(go.Scatter(x=data.index, y=data['Price'], mode='lines', name='Actual'
fig.add_trace(go.Scatter(x=future_dates, y=forecast_95, mode='lines', name='Forecas
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_95.iloc[:, 0], mode='lines', na
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_95.iloc[:, 1], mode='lines', na
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_90.iloc[:, 0], mode='lines', na
fig.add_trace(go.Scatter(x=future_dates, y=conf_int_90.iloc[:, 1], mode='lines', na
fig.update_layout(title='Brent Crude Oil Price Forecast (with Confidence Intervals)
```

```
fig.show()




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

# Plot actual data
plt.plot(data.index, data['Price'], label='Actual')

# Plot forecast
plt.plot(future_dates, forecast_95, label='Forecast')

# Plot 95% confidence interval
plt.fill_between(future_dates, conf_int_95.iloc[:, 0], conf_int_95.iloc[:, 1], colo

# Plot 90% confidence interval
plt.fill_between(future_dates, conf_int_90.iloc[:, 0], conf_int_90.iloc[:, 1], colo

plt.title('Brent Crude Oil Price Forecast (with Confidence Intervals)')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend(loc='best')
```

Out[ ]: <matplotlib.legend.Legend at 0x210679fa3e0>



In [ ]:

In [ ]: