Modelling and Forecasting Brent Crude Oil with Random Forest Regressor

1. Importing Libraries: The first step is to import the necessary libraries. These libraries provide the tools and functions needed to perform the tasks in the code.

- `sklearn.model_selection.RandomizedSearchCV` : This is a function for performing randomized search on hyperparameters. It is used to find the best parameters for the model.
- `sklearn.metrics.mean_absolute_error` , `mean_absolute_percentage_error` , `mean_squared_error` : These are functions for calculating different types of error metrics between the actual and predicted values.
- `sklearn.ensemble.RandomForestRegressor` : This is the Random Forest regression model from the sklearn library.
- `numpy` : This is a library for numerical computations in Python.
- `plotly.graph_objects` and `plotly.express` : These are libraries for creating interactive plots.
- `pandas` : This is a library for data manipulation and analysis.

In [ ]:
```
#%%
# Importing libraries
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error, me
from sklearn.ensemble import RandomForestRegressor
import numpy as np
import plotly.graph_objects as go
import plotly.express as px
import pandas as pd
import plotly.offline as py
# py.init_notebook_mode()
```

2. **Loading Data**: The data is loaded from a CSV file into a pandas DataFrame.

- The parse_dates=True argument is used to automatically parse dates in the CSV file, and `index_col=[0]` sets the first (0th) column as the index of the DataFrame.

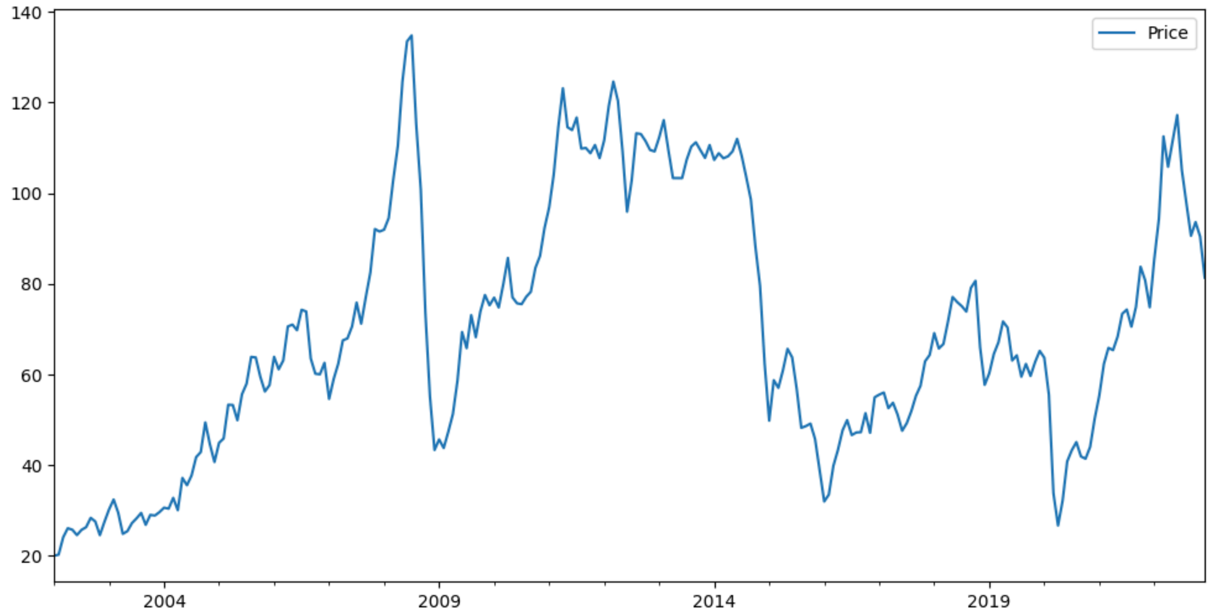
In [ ]:
```
#%%
# Importing data
data = pd.read_csv('Modified_Data.csv', parse_dates=True, index_col=[0])
```

3. **Visualize Data**: Plot the data with price on the y axis and dates on the x axis

In [ ]:
```
# px.line(data, x=data.index, y='Price', title='Prices of Brent Crude Oil from 2002
```

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

Out[ ]: <Axes: >



4. **Setting Train and Test Dates**: The start dates for the training and test datasets are defined.

In [ ]:
```
#%%
# Set dates for training and testing
train_start_date = '2002-01-01'
test_start_date = '2019-01-01'
```

5. **Creating Train and Test Datasets**: The data is split into training and test datasets based on the defined start dates.

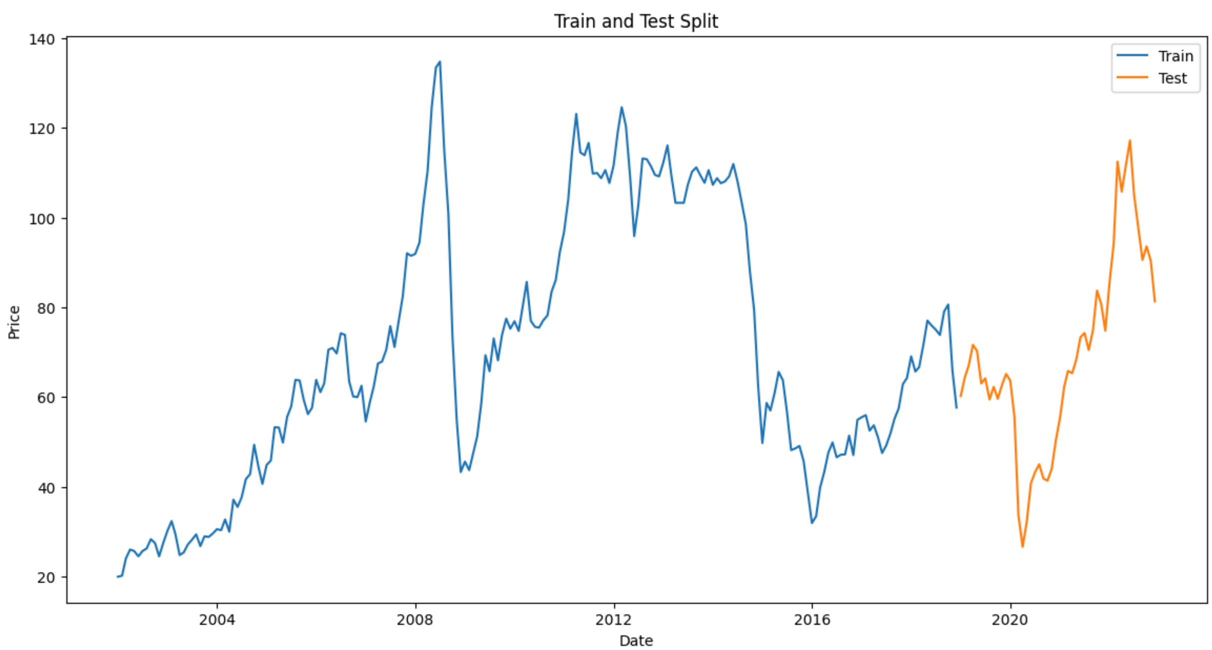
- The training dataset includes all data from the start date to the day before the test start date.
- The test dataset includes all data from the test start date onwards.

In [ ]:
```
#%%

# 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)
```

6. **Visualize Training and Testing Sets**: Plot the train and testing sets on a graph

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()


import matplotlib.pyplot as plt

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()
```



7. **Creating Timesteps**: The data is reshaped into a 3D array where the third dimension represents the timesteps. This is done for both the training and test datasets.

- The concept of "timesteps" is used to define the number of time periods to look back in the data to make a prediction. This is also known as the "lag".
- For example, if you're predicting monthly sales and you set timesteps to 12, the model will use the sales of the previous 12 months to predict the sales of the next month.

In [ ]:
```
#%%

# Set the timesteps
timesteps = 24
```

```
# Convert the data to numpy array
train_data = train.values
test_data = test.values

# Create timesteps for the train data
train_data_timesteps = np.array([[j for j in train_data[i:i+timesteps]] for i in ra

# Create timesteps for the test data
test_data_timesteps = np.array([[j for j in test_data[i:i+timesteps]] for i in rang
```

8. **Splitting Data into Features and Target**: The data is split into features (X) and target (y) for both the training and test datasets. The target is the last timestep and the features are all the other timesteps.

In [ ]:

```
# Split the data into features and target
X_train, y_train = train_data_timesteps[:,:timesteps-1],train_data_timesteps[:,[tim

X_test, y_test = test_data_timesteps[:,:timesteps-1],test_data_timesteps[:,[timeste

#to avoid the warning
y_train = y_train.ravel()
y_test = y_test.ravel()
```

▶ Overview of Random Forests

▶ Visualizing the Journey: The Flowchart

9. **Setting Up the Model**: A Random Forest Regressor model is set up and a RandomizedSearchCV is used to find the best parameters for the model.

How the parameters in `param_dist_rf` work

1. `n_estimators` : The number of trees in the forest. More trees reduce the variance of predictions, improving the model's performance. However, too many trees can slow down the model without providing much benefit.

2. `max_depth` : The maximum depth of the trees. Deeper trees can model more complex patterns, but they're also more likely to overfit to the training data.

3. `max_features` : The number of features to consider when looking for the best split. Considering more features at each split can increase the model's flexibility, but it can also slow down the training process.

4. `min_samples_split` : The minimum number of samples required to split an internal node. Larger values can help prevent overfitting, but if they're too large, the model might underfit.

5. `bootstrap` : Whether bootstrap samples are used when building trees. If False, the whole dataset is used to build each tree.

In [ ]:
```
from sklearn.model_selection import TimeSeriesSplit, RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor
import numpy as np

# Define the hyperparameters for the RandomizedSearchCV
param_dist_rf = {"n_estimators": np.random.randint(450, 500, size=10), # Number of
                 "max_depth": np.append(np.random.randint(1, 5, size=5), None), # M
                 "max_features": np.random.randint(1, 11, size=10), # Number of fea
                 "min_samples_split": np.random.randint(2, 11, size=10), # Minimum
                 "bootstrap": [True, False]} # Method of selecting samples for trai

rf = RandomForestRegressor(random_state=42) # Instantiate the model

tscv = TimeSeriesSplit(n_splits=5) # Instantiate TimeSeriesSplit

random_search_rf = RandomizedSearchCV(rf, param_distributions=param_dist_rf,
                                      n_iter=10, cv=tscv, random_state=42) # Instan
```

10. **Training the Model**: The model is trained on the training data.

In [ ]:
```
#%%
# Fit the model
random_search_rf.fit(X_train, y_train)
best_rf = random_search_rf.best_estimator_
# Predict the test data
best_rf.fit(train_data_timesteps[:,:timesteps-1], train_data_timesteps[:,[timesteps
```

```
d:\DEV WORK\Data Science Library\ML-For-Beginners\.venv\lib\site-packages\sklearn\ba
se.py:1351: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape o
f y to (n_samples,), for example using ravel().
```

Out[ ]:
```
RandomForestRegressor

RandomForestRegressor(max_features=10, min_samples_split=10, n_estimators=
494,
                      random_state=42)
```

11. **Making Predictions**: The model is used to make predictions on the test data with the best parameters

In [ ]:
```
#%%
# Predict the test data
rf_predictions = best_rf.predict(test_data_timesteps[:,:timesteps-1])
```

12. **Evaluating the Model**: The model's predictions are compared to the actual values to calculate the

- root mean squared error (RMSE)
- mean absolute error (MAE), and
- mean absolute percentage error (MAPE).

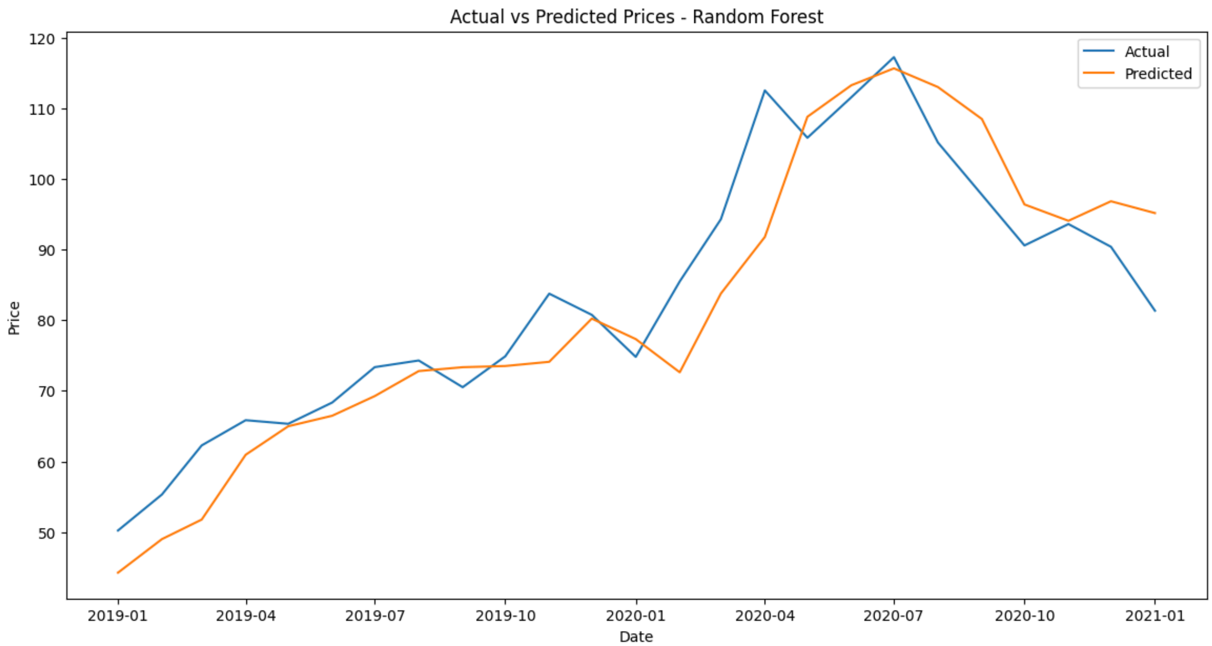
In [ ]:
```
#%%
# Calculate the evaluation metrics
mse_rf = mean_squared_error(test_data_timesteps[:,[timesteps-1]], rf_predictions)
rmse_rf = np.sqrt(mean_squared_error(test_data_timesteps[:,[timesteps-1]], rf_predi
mae_rf = mean_absolute_error(test_data_timesteps[:,[timesteps-1]], rf_predictions)
mape_rf = mean_absolute_percentage_error(test_data_timesteps[:,[timesteps-1]], rf_p
directional_accuracy_rf = np.mean(np.sign(test_data_timesteps[:,[timesteps-1]] - rf
print(f'Random Forest MSE: {mse_rf:.3f}')
print(f'Random Forest RMSE: {rmse_rf:.3f}')
print(f'Random Forest MAE: {mae_rf:.3f}')
print(f'Random Forest MAPE: {mape_rf *100:.3f}%')
print(f'Random Forest Directional Accuracy: {directional_accuracy_rf *100:.3f}%')
```

```
Random Forest MSE: 60.193
Random Forest RMSE: 7.758
Random Forest MAE: 5.914
Random Forest MAPE: 7.184%
Random Forest Directional Accuracy: 52.320%
```

13. **Visualizing the Results**: The actual and predicted prices are plotted over time.

In [ ]:
```
#%%

# Plot the actual vs predicted prices with plotly
# fig = go.Figure()
# fig.add_trace(go.Scatter(x=test.index, y=test_data_timesteps[:,[timesteps-1]].fla
# fig.add_trace(go.Scatter(x=test.index, y=rf_predictions, mode='lines', name='Pred
# fig.update_layout(title='Actual vs Predicted Prices - Random Forest',
#                   xaxis_title='Date',
#                   yaxis_title='Price')
# fig.show()

# plot with matplotlib
# Get the length of your predictions
pred_length = len(rf_predictions)

# Create a new figure
plt.figure(figsize=(14, 7))

# Plot the actual prices
plt.plot(test.index[:pred_length], test_data_timesteps[:pred_length, [timesteps-1]]

# Plot the predicted prices
plt.plot(test.index[:pred_length], rf_predictions, label='Predicted')
```

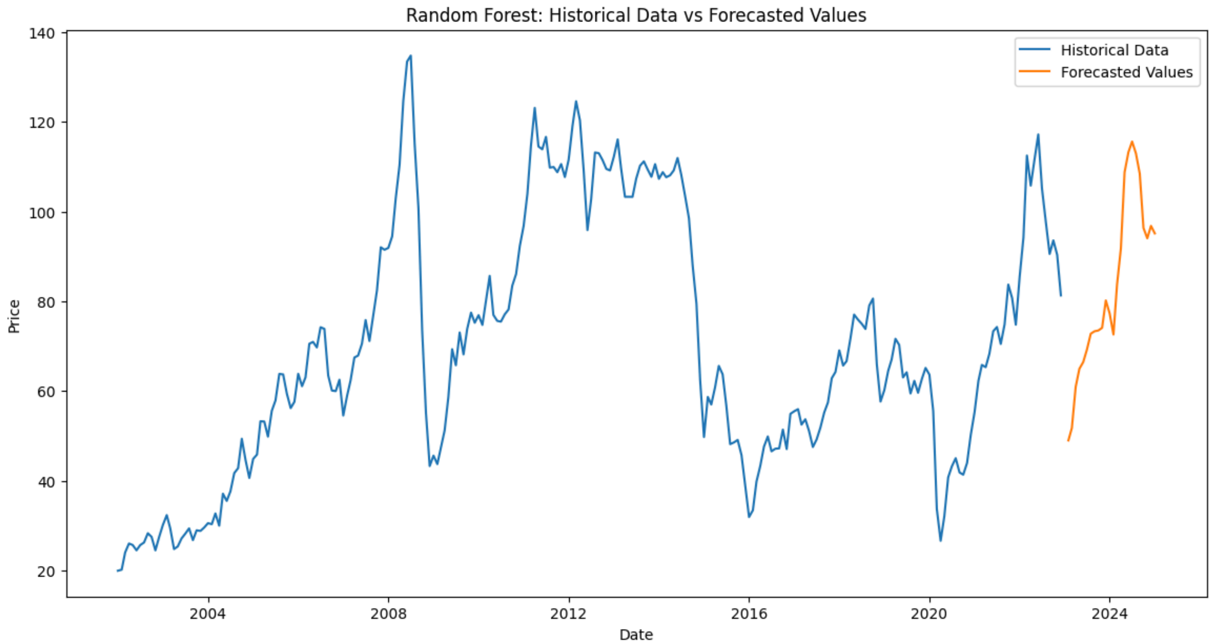
```python
# Set the title and labels
plt.title('Actual vs Predicted Prices - Random Forest')
plt.xlabel('Date')
plt.ylabel('Price')

# Add a legend
plt.legend(loc='best')

# Display the plot
plt.show()
```



14. **Forecasting Future Prices**: The model is used to forecast prices for the next 24 months. The forecasted prices are then plotted along with the historical data.

In [ ]:
```python
#%%

future_dates = pd.date_range(start=data.index[-1], periods=25, freq='M')[1:] # Star

# Make predictions on the future data
rf_forecast = best_rf.predict(test_data_timesteps[-24:,:timesteps-1])

# Plot the historical data and the forecasted data for each model individually
# fig_rf = go.Figure()
# fig_rf.add_trace(go.Scatter(x=data.index, y=data['Price'], mode='lines', name='Hi
# fig_rf.add_trace(go.Scatter(x=future_dates, y=rf_forecast, mode='lines', name='Fo
# fig_rf.update_layout(title='Random Forest: Historical Data vs Forecasted Values')
# fig_rf.show()

# plot with matplotlib

# import matplotlib.pyplot as plt

plt.figure(figsize=(14, 7))
plt.plot(data.index, data['Price'], label='Historical Data')
```

```
plt.plot(future_dates, rf_forecast, label='Forecasted Values')
plt.title('Random Forest: Historical Data vs Forecasted Values')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend(loc='best')
plt.show()
```



In [ ]: