Final_DAT301_Finance

December 6, 2024

[37]:
```
# Import necessary libraries
import yfinance as yf
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, make_scorer
```

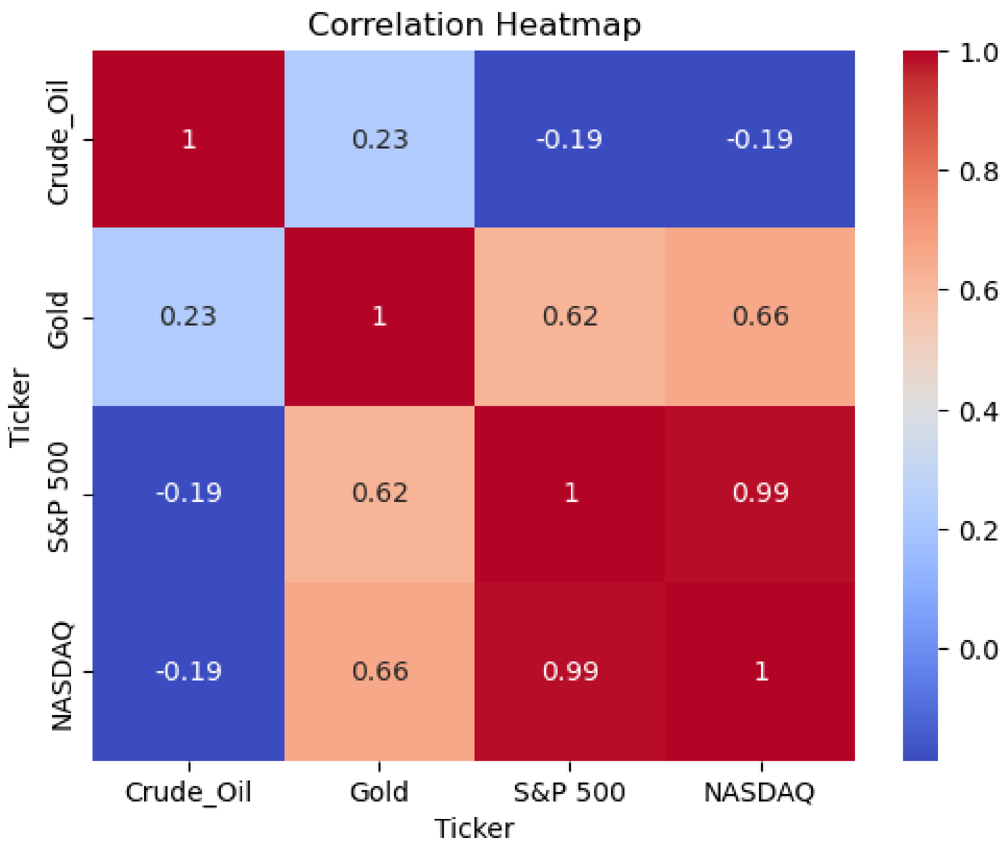
[58]:
```
#The goal of this project is to make a machine learning forecast in order to␣
↪predict the future value of the S&P 500. We will use information from␣
↪various commodities such as Oil and Gold; then we will compare it with a␣
↪model that has plenty more information such as palladium and platinum among␣
↪other things. We will then look at the differences between the two models␣
↪and observe which one was more accurate.
```

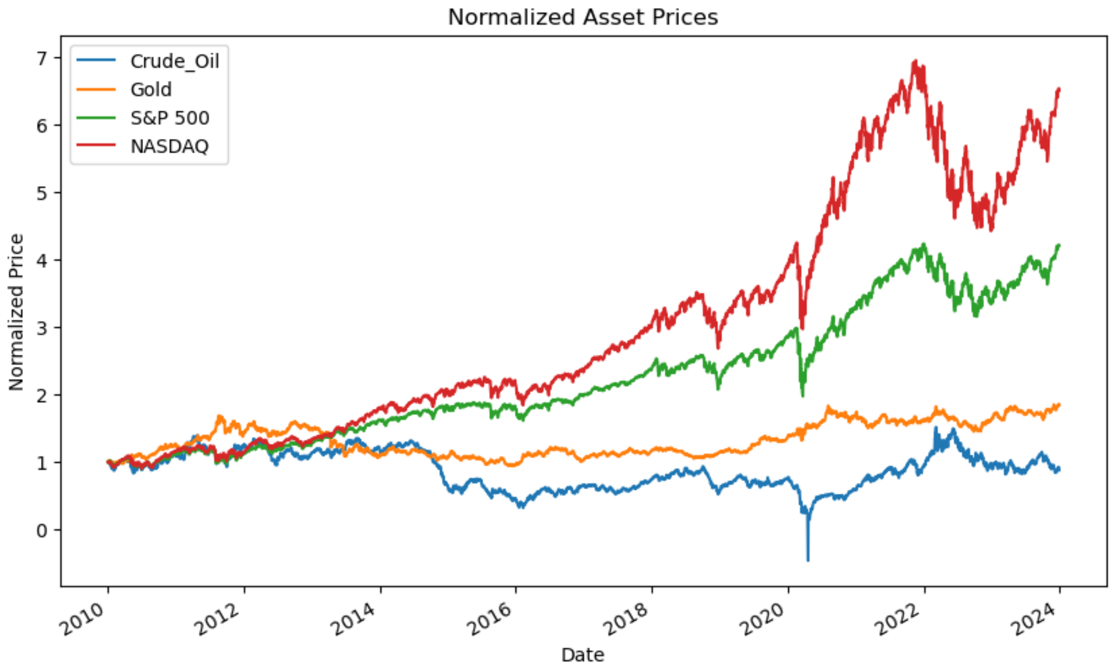
[38]:
```
# Download and preprocess data

# Download financial data for S&P 500, NASDAQ, Gold, and Crude Oil
assets = ['^GSPC', '^IXIC', 'GC=F', 'CL=F']
asset_names = {'^GSPC': 'S&P 500', '^IXIC': 'NASDAQ', 'GC=F': 'Gold', 'CL=F':␣
↪'Crude_Oil'}

data = yf.download(assets, start='2010-01-01', end='2023-12-31')['Adj Close']
data.rename(columns=asset_names, inplace=True)
data.fillna(method='ffill', inplace=True)  # Handle missing values

# Normalize data for comparison
normalized_data = data / data.iloc[0]
```

```
[*********************100%***********************]  4 of 4 completed
C:\Users\regg0\AppData\Local\Temp\ipykernel_48992\327991134.py:9: FutureWarning:
DataFrame.fillna with 'method' is deprecated and will raise in a future version.
Use obj.ffill() or obj.bfill() instead.
  data.fillna(method='ffill', inplace=True)  # Handle missing values
```

[39]:
```
# Visualize correlations
correlation = normalized_data.corr()
```

```python
sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()

# Plot normalized trends
normalized_data.plot(figsize=(10, 6), title="Normalized Asset Prices")
plt.ylabel('Normalized Price')
plt.xlabel('Date')
plt.legend(loc='upper left')
plt.show()
```





[ ]:

```
#With the corralation map created above, you can see that gold have a far
 ↪amount of correlation with both the S&P 500 and the NASSDAQ.
#Crude Oil has almost no correlation which is seen by the negative value
 ↪attached to it above.
#Finally, you can see that the S&P 500 abd NASDAQ has almost perfect
 ↪correlation denoted by the 0.99 score attached to them.
#Afterwards,plotted the Asset trends over the last 14 years.
#Interestingly, while Crude Oil, S&P 500 and Nasdaq all dropped drasticly in
 ↪2021 Gold contiuned to grow; just like the reputation of gold it always stay
 ↪steady.
```

[40]:

```
# Feature Engineering
data['Gold_Rolling'] = data['Gold'].rolling(window=5).mean()
data['Crude_Lagged'] = data['Crude_Oil'].shift(1)
data['Gold_Lagged_2'] = data['Gold'].shift(2)
data['Crude_Rolling_10'] = data['Crude_Oil'].rolling(window=10).mean()
data['SPY_Daily_Return'] = data['S&P 500'].pct_change()
data['Gold_Volatility'] = data['Gold'].rolling(window=5).std()

# Drop NaN rows introduced by feature engineering
data.dropna(inplace=True)

# Prepare features and target
X = data[['Gold', 'Gold_Rolling', 'Crude_Lagged', 'Gold_Lagged_2',
 ↪'Crude_Rolling_10', 'SPY_Daily_Return', 'Gold_Volatility']]
```

```
Y = data['S&P 500']

# Train-test split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=42)

# Train Random Forest model
model = RandomForestRegressor(random_state=42)
model.fit(X_train, Y_train)
```

[40]:
```
RandomForestRegressor(random_state=42)
```

[41]:
```
# Cross-validation
cv = KFold(n_splits=5, shuffle=True, random_state=42)
mse_scorer = make_scorer(mean_squared_error, greater_is_better=False)
cv_scores = cross_val_score(model, X, Y, cv=cv, scoring=mse_scorer)
print("Mean RMSE across folds:", (-cv_scores.mean()) ** 0.5)

# Make predictions
Y_pred = model.predict(X_test)
print("RMSE:", mean_squared_error(Y_test, Y_pred, squared=False))
print("R^2 Score:", r2_score(Y_test, Y_pred))
```

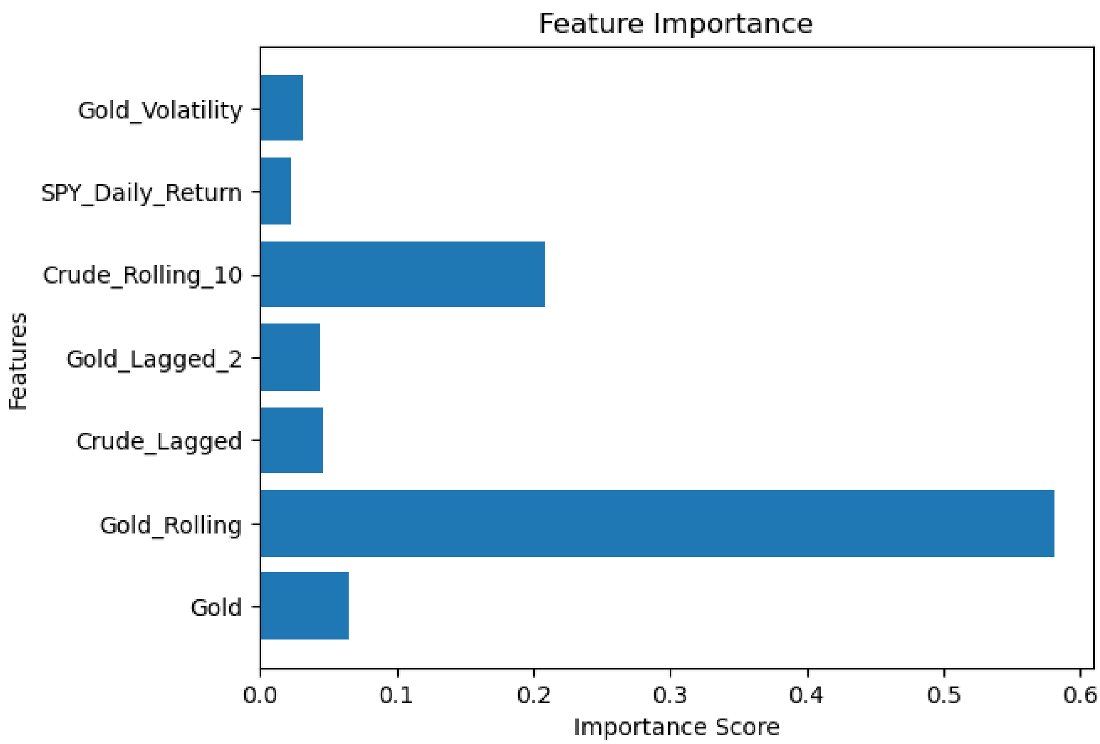
```
Mean RMSE across folds: 401.228691792886
RMSE: 422.0505841105682
R^2 Score: 0.8415046674116458
```

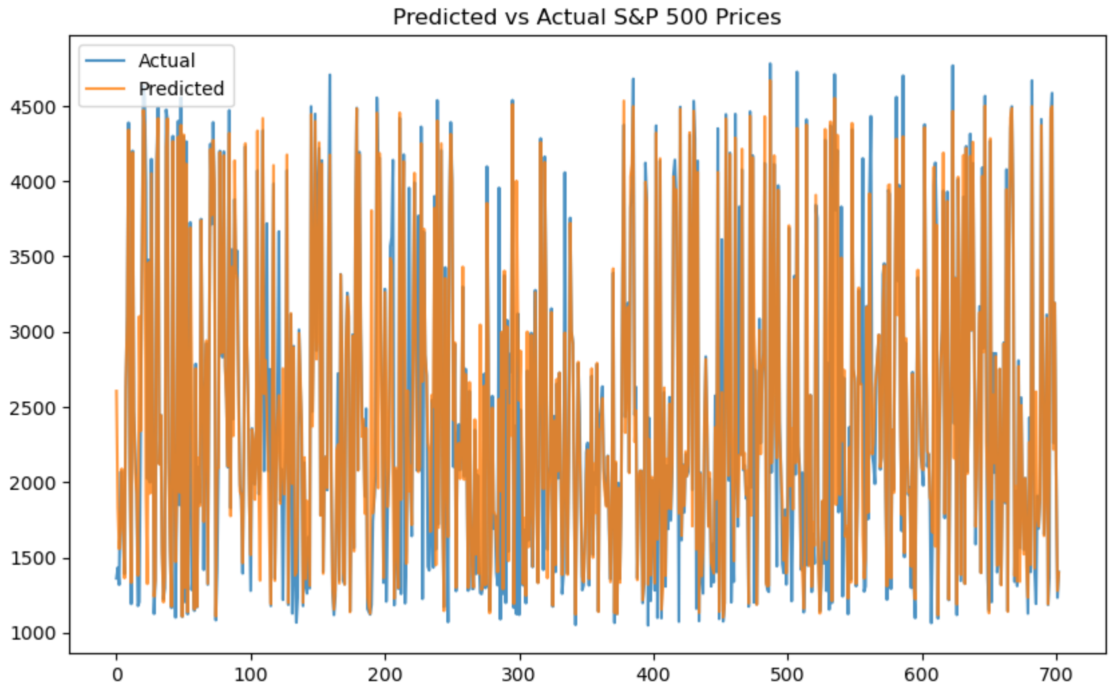
```
C:\Users\regg0\anaconda3\Lib\site-packages\sklearn\metrics\_regression.py:492:
FutureWarning: 'squared' is deprecated in version 1.4 and will be removed in
1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
```

[ ]:
```
#With a mean RMSE at about 401.23, the average deviation of the model's␣
↪prediction from the actual value is about 401.23 points. Give that the index␣
↪ranges in the thousands, this level of error is considered to be reasonable.

#With a RMSE of 422.05, the model's predictions differ from the S&P 500 by␣
↪about 422.05 points.

#R^2 Score: 0.8415 means that my model explains about 84.15% of the variance in␣
↪the S&P 500 index
```

[42]:
```
# Feature Importance
importance = model.feature_importances_
features = X.columns
plt.barh(features, importance)
plt.title('Feature Importance')
```

```
plt.xlabel('Importance Score')
plt.ylabel('Features')
plt.show()

# Visualize predicted vs actual
plt.figure(figsize=(10, 6))
plt.plot(Y_test.reset_index(drop=True), label='Actual', alpha=0.8)
plt.plot(pd.Series(Y_pred, index=range(len(Y_pred))), label='Predicted',␣
↪alpha=0.8)
plt.title("Predicted vs Actual S&P 500 Prices")
plt.legend()
plt.show()
```





[61]:
```
#Observations: The predicted values closely overlap or align with the actual␣
↪values for a vast majority
#of the data points.
#The overlapping makes it challenging to see differences between actual and␣
↪predicted values.
#A scatter plot of residuals would make it easier to see the differences.

#Performance: Since the predicted and actual values match well, the model has␣
↪decent predictive accuracy.
#Which is backed up by the scores we calculated earlier.

#Challenges:
#There are several parts of the graph where the model seemed to really struggle␣
↪with predicting see the 550 interval.



# In this next section, I will be feeding the model more datapoints varying␣
↪from different common commodities and stocks that are all related with the␣
↪test being whether it will make the model more accurate or not.
```

```
Cell In[61], line 1
  Observations: The predicted values closely overlap or align with the actual␣
↪values for a vast majority
```

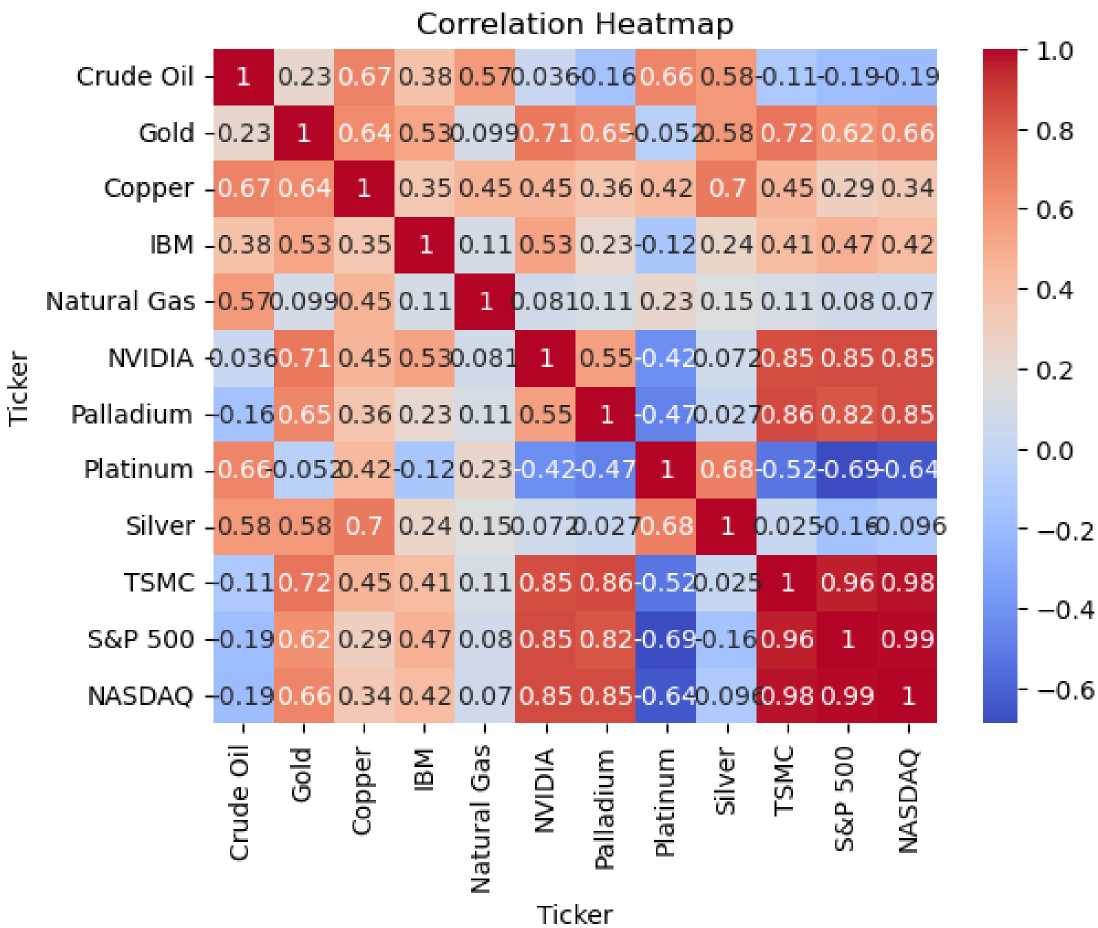
```
                  ^
SyntaxError: invalid syntax
```

[43]:
```python
assets = ['^GSPC', '^IXIC', 'GC=F', 'CL=F', 'SI=F', 'NG=F', 'HG=F', 'PL=F',␣
↪'PA=F','TSM','NVDA','IBM' ]
asset_names = {
    '^GSPC': 'S&P 500',
    '^IXIC': 'NASDAQ',
    'GC=F': 'Gold',
    'CL=F': 'Crude Oil',
    'SI=F': 'Silver',
    'NG=F': 'Natural Gas',
    'HG=F': 'Copper',
    'PL=F': 'Platinum',
    'PA=F': 'Palladium',
    'TSM': 'TSMC',
    'NVDA': 'NVIDIA',
    'IBM': 'IBM'

}


# Download and preprocess data
data = yf.download(assets, start='2010-01-01', end='2023-12-31')['Adj Close']
data.rename(columns=asset_names, inplace=True)
data.fillna(method='ffill', inplace=True)  # Handle missing values

# Normalize data for comparison
normalized_data = data / data.iloc[0]
```

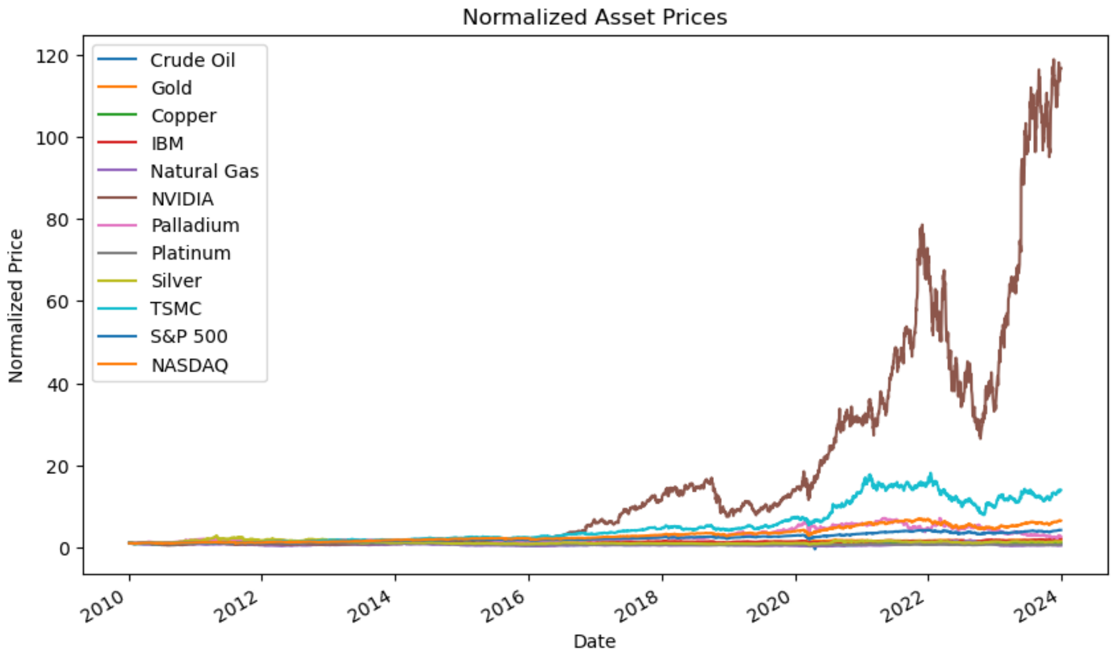
```
[*********************100%***********************]  12 of 12 completed
C:\Users\regg0\AppData\Local\Temp\ipykernel_48992\1726062962.py:22:
FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a
future version. Use obj.ffill() or obj.bfill() instead.
  data.fillna(method='ffill', inplace=True)  # Handle missing values
```

[44]:
```python
# Visualize correlations with Seaborn
sns.heatmap(normalized_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()

# Plot normalized trends with Matplotlib
normalized_data.plot(figsize=(10, 6), title="Normalized Asset Prices")
plt.ylabel('Normalized Price')
plt.xlabel('Date')
plt.legend(loc='upper left')
```

```
plt.show()
```



Correlation Heatmap
Ticker
Crude Oil
Gold
Copper
IBM
Natural Gas
NVIDIA
Palladium
Platinum
Silver
TSMC
S&P 500
NASDAQ
1 0.23 0.67 0.38 0.57 0.036 -0.16 0.66 0.58 -0.11 -0.19 -0.19
0.23 1 0.64 0.53 0.099 0.71 0.65 -0.052 0.58 0.72 0.62 0.66
0.67 0.64 1 0.35 0.45 0.45 0.36 0.42 0.7 0.45 0.29 0.34
0.38 0.53 0.35 1 0.11 0.53 0.23 -0.12 0.24 0.41 0.47 0.42
0.57 0.099 0.45 0.11 1 0.081 0.11 0.23 0.15 0.11 0.08 0.07
0.036 0.71 0.45 0.53 0.081 1 0.55 -0.42 0.072 0.85 0.85 0.85
-0.16 0.65 0.36 0.23 0.11 0.55 1 -0.47 0.027 0.86 0.82 0.85
0.66 -0.052 0.42 -0.12 0.23 -0.42 -0.47 1 0.68 -0.52 -0.69 -0.64
0.58 0.58 0.7 0.24 0.15 0.072 0.027 0.68 1 0.025 -0.16 0.096
-0.11 0.72 0.45 0.41 0.11 0.85 0.86 -0.52 0.025 1 0.96 0.98
-0.19 0.62 0.29 0.47 0.08 0.85 0.82 -0.69 -0.16 0.96 1 0.99
-0.19 0.66 0.34 0.42 0.07 0.85 0.85 -0.64 0.096 0.98 0.99 1
Crude Oil
Gold
Copper
IBM
Natural Gas
NVIDIA
Palladium
Platinum
Silver
TSMC
S&P 500
NASDAQ
Ticker
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6



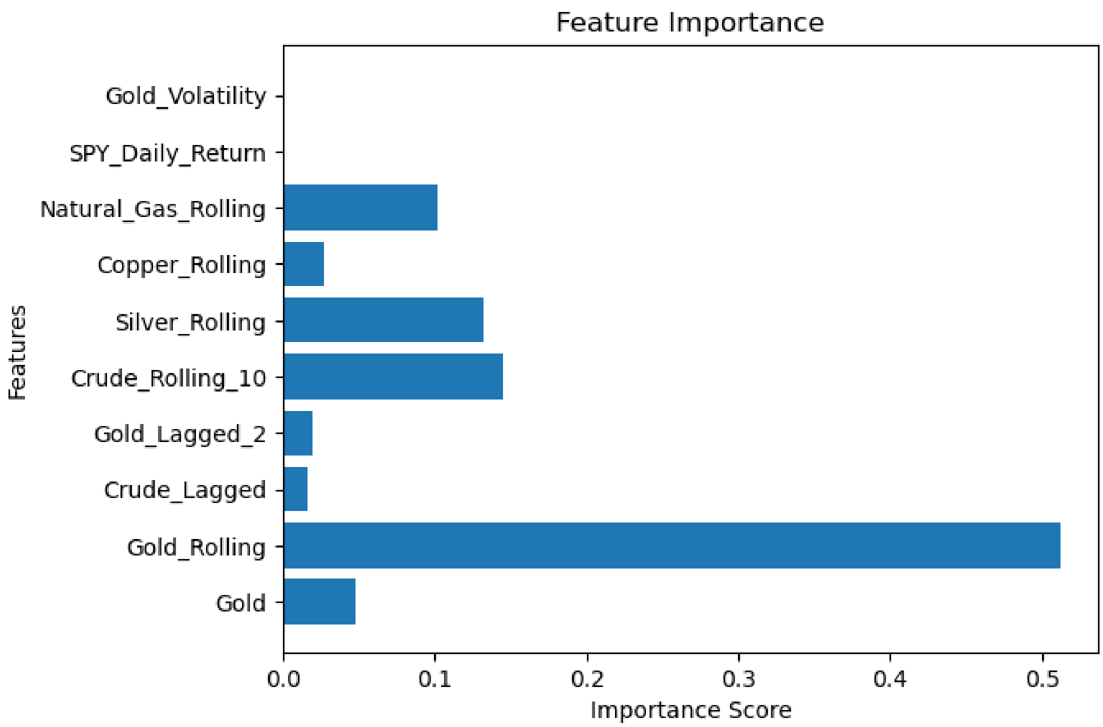

```
[ ]: #With the heat map you can see that alot of the new data points added were␣
     ↪strongly correlated to the major stock markets that I am using.
     #This was on purpose to see if this would lead to a better prediction.
```

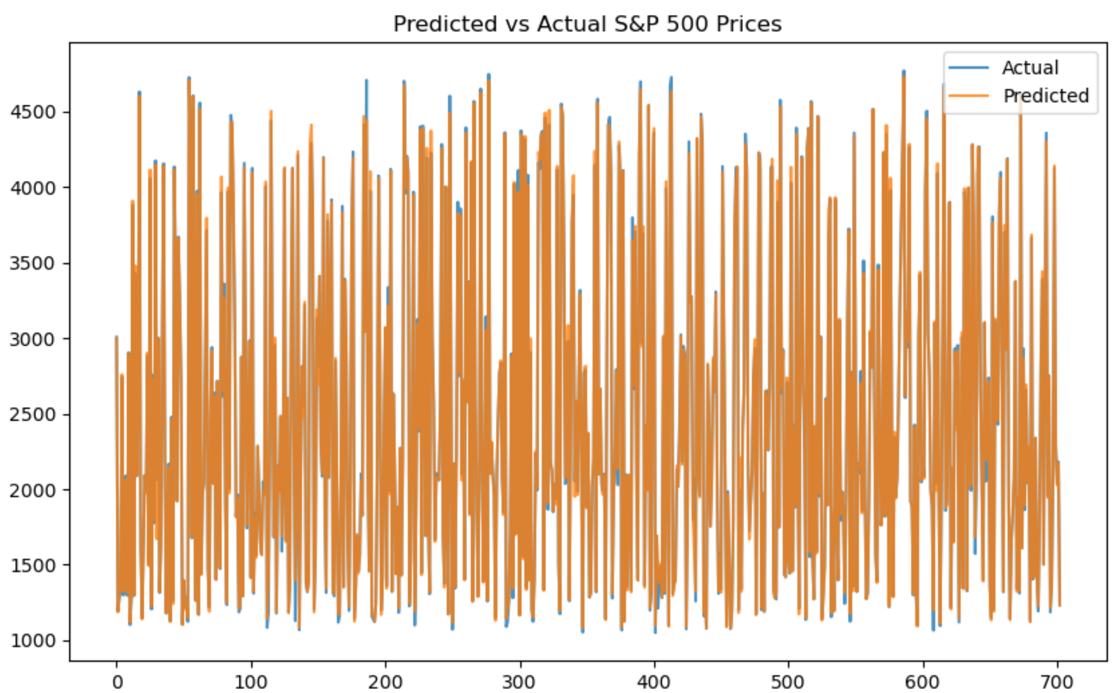
```
[45]: # Feature Engineering
      data['Gold_Rolling'] = data['Gold'].rolling(window=5).mean()
      data['Crude_Lagged'] = data['Crude Oil'].shift(1)
      data['Gold_Lagged_2'] = data['Gold'].shift(2)
      data['Crude_Rolling_10'] = data['Crude Oil'].rolling(window=10).mean()
      data['Silver_Rolling'] = data['Silver'].rolling(window=5).mean()
      data['Copper_Rolling'] = data['Copper'].rolling(window=5).mean()
      data['Natural_Gas_Rolling'] = data['Natural Gas'].rolling(window=5).mean()
      data['SPY_Daily_Return'] = data['S&P 500'].pct_change()
      data['Gold_Volatility'] = data['Gold'].rolling(window=5).std()

      # Drop NaN rows introduced by feature engineering
      data.dropna(inplace=True)

      # Prepare features and target
      X = data[['Gold', 'Gold_Rolling', 'Crude_Lagged', 'Gold_Lagged_2',␣
       ↪'Crude_Rolling_10', 'Silver_Rolling', 'Copper_Rolling',␣
       ↪'Natural_Gas_Rolling', 'SPY_Daily_Return', 'Gold_Volatility',]]
      Y = data['S&P 500']

      # Train-test split
```

```python
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)

# Train Random Forest model
model = RandomForestRegressor(random_state=42)
model.fit(X_train, Y_train)

# Cross-validation
cv = KFold(n_splits=5, shuffle=True, random_state=42)
mse_scorer = make_scorer(mean_squared_error, greater_is_better=False)
cv_scores = cross_val_score(model, X, Y, cv=cv, scoring=mse_scorer)
print("Mean RMSE across folds:", (-cv_scores.mean()) ** 0.5)

# Make predictions
Y_pred = model.predict(X_test)
print("RMSE:", mean_squared_error(Y_test, Y_pred, squared=False))
print("R^2 Score:", r2_score(Y_test, Y_pred))

# Feature Importance
importance = model.feature_importances_
features = X.columns
plt.barh(features, importance)
plt.title('Feature Importance')
plt.xlabel('Importance Score')
plt.ylabel('Features')
plt.show()



# Visualize predicted vs actual with Matplotlib
plt.figure(figsize=(10, 6))
plt.plot(Y_test.reset_index(drop=True), label='Actual', alpha=0.8)
plt.plot(pd.Series(Y_pred, index=range(len(Y_pred))), label='Predicted', alpha=0.8)
plt.title("Predicted vs Actual S&P 500 Prices")
plt.legend()
plt.show()
```

```
Mean RMSE across folds: 68.71091212001345
RMSE: 52.76883209522988
R^2 Score: 0.9976367481929272
```

```
C:\Users\regg0\anaconda3\Lib\site-packages\sklearn\metrics\_regression.py:492:
FutureWarning: 'squared' is deprecated in version 1.4 and will be removed in
1.6. To calculate the root mean squared error, use the
function'root_mean_squared_error'.
  warnings.warn(
```


Feature Importance
Gold_Volatility
SPY_Daily_Return
Natural_Gas_Rolling
Copper_Rolling
Silver_Rolling
Crude_Rolling_10
Gold_Lagged_2
Crude_Lagged
Gold_Rolling
Gold
Features
0.0
0.1
0.2
0.3
0.4
0.5
Importance Score


Predicted vs Actual S&P 500 Prices
Actual
Predicted
4500
4000
3500
3000
2500
2000
1500
1000
0
100
200
300
400
500
600
700

[ ]:

```
#Mean RMSE across folds: 68.71

#This represents the average RSME. A lower value indicates better performance,
↪and 68.71 suggests the model consistently predicts well across folds. This
↪also compared very well against the 420 score the other model had; showing
↪that this model is much improved
#Overall RMSE: 52.77

#This is the root mean squared error for the final model. It shows the standard
↪deviation of the residuals. A value of 52.77 is quite low compared to the
↪scale of S&P 500 prices indicating strong performance. This is further seen
↪that my other model has a much higher score of 420.
#R² Score: 0.9976

#This measures the proportion of variance in the actual prices that the model
↪explains. An R² score close to 1 (like 0.9976) means the model fits the data
↪extremely well, capturing nearly all variability in the actual prices. Which
↪is postive news.
```

[ ]:

```
```