

Import Library

```
In [1]: 1 %matplotlib inline
2 import pandas as pd
3 import numpy as np
4 import seaborn as sns
5 import matplotlib.pyplot as plt
6 import yfinance as yf
7 from datetime import datetime, timedelta
8
9 import warnings
10 warnings.filterwarnings('ignore')
11 np.random.seed(42)
```

Load dataset

```
In [2]: 1 ticker = 'GC=F'
2 end_date = datetime.today().strftime('%Y-%m-%d')
3
4 gold_data = yf.download(ticker, start='2004-01-01', end=end_date)
5
6 goldDF = pd.DataFrame(gold_data).reset_index()
7
8 goldDF
```

[*****100%*****] 1 of 1 completed

Out [2]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2004-01-05	415.700012	422.500000	422.500000	424.399994	424.399994	20
1	2004-01-06	424.399994	424.299988	424.299988	422.799988	422.799988	20
2	2004-01-07	423.000000	423.000000	423.000000	421.899994	421.899994	20
3	2004-01-08	421.899994	422.000000	422.000000	424.000000	424.000000	20
4	2004-01-09	424.000000	423.899994	423.899994	426.399994	426.399994	20
...
5033	2024-01-15	2051.699951	2054.800049	2051.699951	2054.800049	2054.800049	390
5034	2024-01-16	2051.699951	2054.800049	2026.000000	2026.000000	2026.000000	46
5035	2024-01-17	2026.500000	2026.500000	2002.599976	2002.599976	2002.599976	764
5036	2024-01-18	2012.800049	2018.599976	2009.500000	2018.599976	2018.599976	1474
5037	2024-01-19	2023.199951	2036.000000	2019.500000	2026.500000	2026.500000	1474

5038 rows × 7 columns

Exploratory Data Analysis (EDA)

```
In [3]: 1 # Display data types
        2 goldDF.dtypes
```

```
Out[3]: Date          datetime64[ns]
Open            float64
High            float64
Low             float64
Close           float64
Adj Close       float64
Volume          int64
dtype: object
```

```
In [4]: 1 # Display information about the DataFrame
        2 goldDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5038 entries, 0 to 5037
Data columns (total 7 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Date            5038 non-null  datetime64[ns]
1   Open            5038 non-null  float64
2   High            5038 non-null  float64
3   Low             5038 non-null  float64
4   Close           5038 non-null  float64
5   Adj Close       5038 non-null  float64
6   Volume          5038 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 275.6 KB
```

Data Cleaning

```
In [5]: 1 # Checking for missing values
        2 missing_values = goldDF.isnull().sum()
        3 print("Missing Values:\n", missing_values)
```

```
Missing Values:
Date          0
Open          0
High          0
Low           0
Close         0
Adj Close     0
Volume        0
dtype: int64
```

```
In [6]: 1 # Handling missing values (if have)
        2 goldDF = goldDF.dropna()
```

```
In [7]: 1 # Summary statistics
        2 summary_stats = goldDF.describe()
        3 print("Summary Statistics:\n", summary_stats)
```

Summary Statistics:

	Date	Open	High	
Low \				
count	5038	5038.000000	5038.000000	503
8.000000				
mean	2014-01-14 13:22:01.953156096	1242.537277	1248.790294	123
5.903593				
min	2004-01-05 00:00:00	375.799988	375.799988	37
5.799988				
25%	2009-01-13 06:00:00	921.300003	926.600006	91
5.225006				
50%	2014-01-14 12:00:00	1269.799988	1274.649963	126
4.750000				
75%	2019-01-21 00:00:00	1629.174957	1641.125031	161
9.675049				
max	2024-01-19 00:00:00	2081.600098	2130.199951	206
6.500000				
std	NaN	454.465985	456.898311	45
1.944020				

	Close	Adj Close	Volume
count	5038.000000	5038.000000	5038.000000
mean	1242.398233	1242.398233	4802.149266
min	374.799988	374.799988	0.000000
25%	922.225006	922.225006	30.250000
50%	1270.400024	1270.400024	127.000000
75%	1628.100037	1628.100037	437.750000
max	2081.899902	2081.899902	386334.000000
std	454.423420	454.423420	26130.262789

```
In [8]: 1 goldDF.std()
```

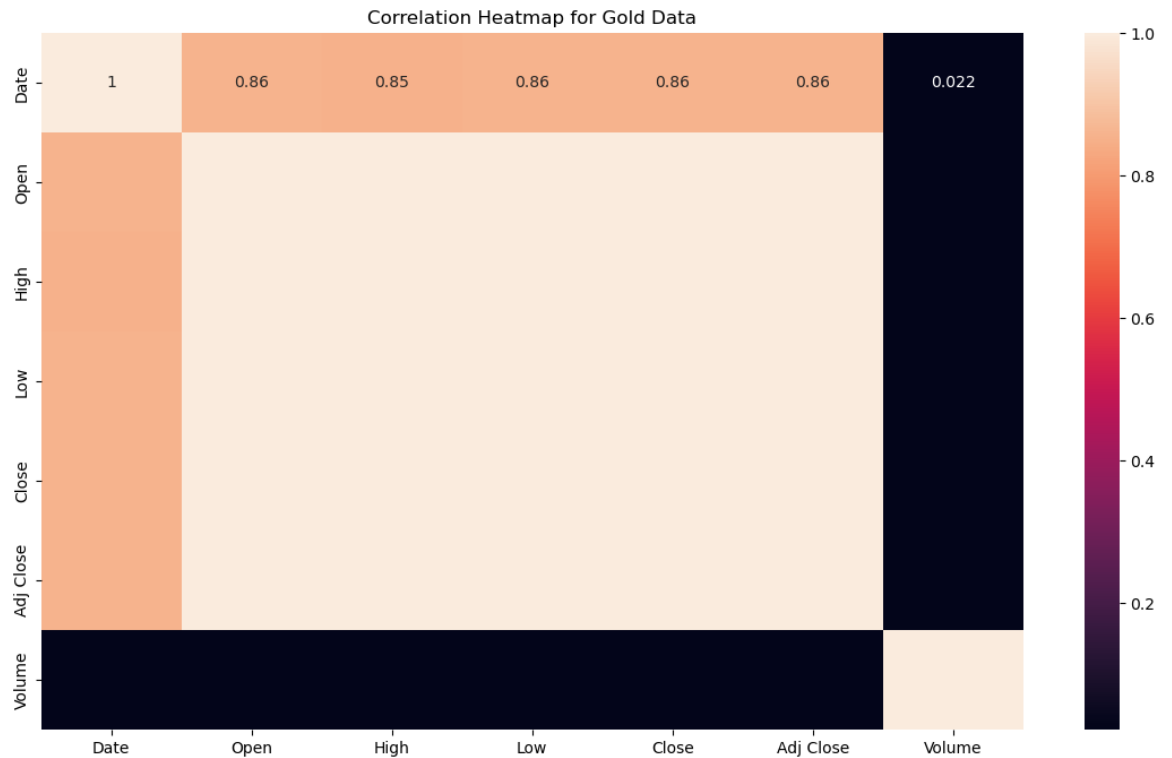
Out [8]: Date 2112 days 23:12:11.356896672
Open 454.465985
High 456.898311
Low 451.94402
Close 454.42342
Adj Close 454.42342
Volume 26130.262789
dtype: object

Statistical Analysis and Hypothesis Testing

```
In [9]: 1 # Calculate mean and standard deviation difference
        2 mean_difference = (goldDF['Adj Close'] - goldDF['Close']).mean()
        3 std_difference = (goldDF['Adj Close'] - goldDF['Close']).std()
        4
        5 print(f"Mean Difference: {mean_difference:.2f} USD")
        6 print(f"Standard Deviation of Difference: {std_difference:.2f} USD")
```

Mean Difference: 0.00 USD
Standard Deviation of Difference: 0.00 USD

```
In [10]: 1 goldDF_corr = goldDF.corr()
2 goldDF_corr
3
4 plt.figure(figsize=(14, 8))
5 sns.heatmap(goldDF_corr, annot=True)
6
7 plt.title('Correlation Heatmap for Gold Data')
8 plt.show()
```



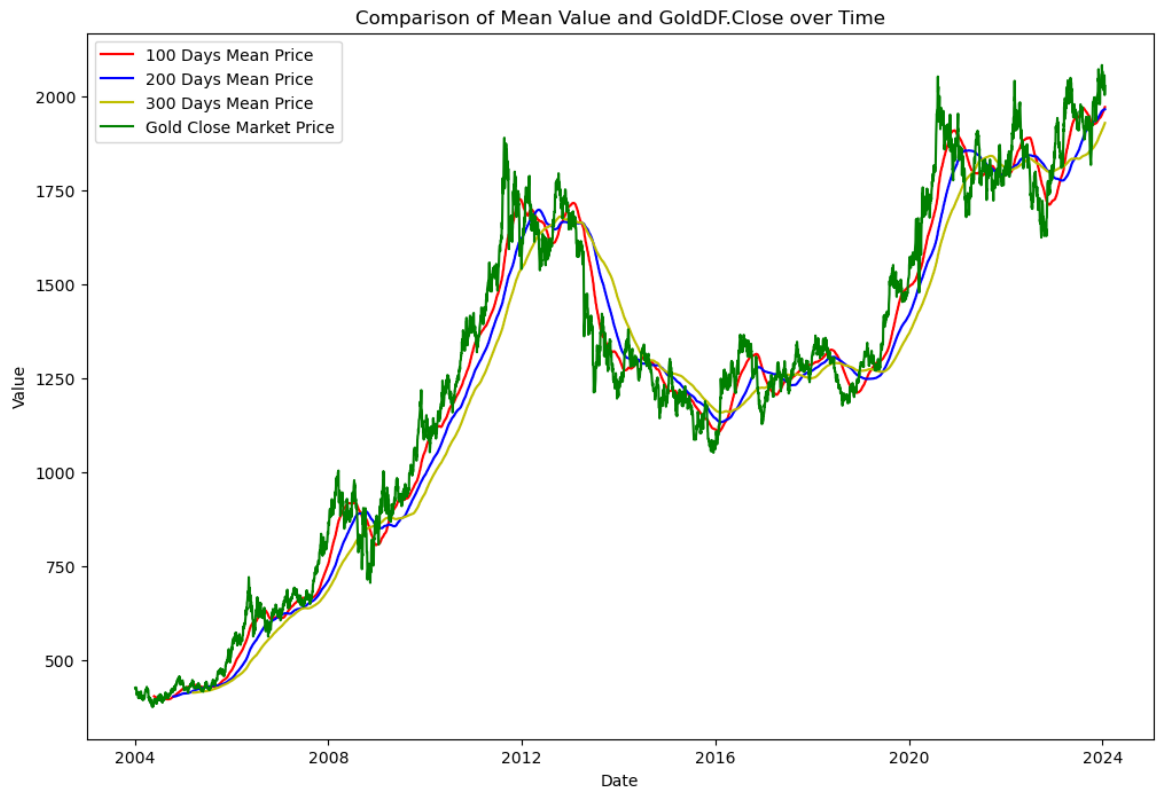
Model Selection and Development

```
In [11]: 1 # Calculate moving averages
2 maen100Days = goldDF['Close'].rolling(100).mean()
3 maen200Days = goldDF['Close'].rolling(200).mean()
4 maen300Days = goldDF['Close'].rolling(300).mean()
```

```

In [12]: 1 # Plot mean values and gold close prices over time
2 plt.figure(figsize=(12, 8))
3
4 plt.plot(goldDF['Date'], maen100Days, 'r', label='100 Days Mean Price')
5 plt.plot(goldDF['Date'], maen200Days, 'b', label='200 Days Mean Price')
6 plt.plot(goldDF['Date'], maen300Days, 'y', label='300 Days Mean Price')
7
8 plt.plot(goldDF['Date'], goldDF['Close'], 'g', label='Gold Close Market Price')
9
10 plt.title('Comparison of Mean Value and GoldDF.Close over Time')
11 plt.xlabel('Date')
12 plt.ylabel('Value')
13 plt.legend()
14 plt.show()

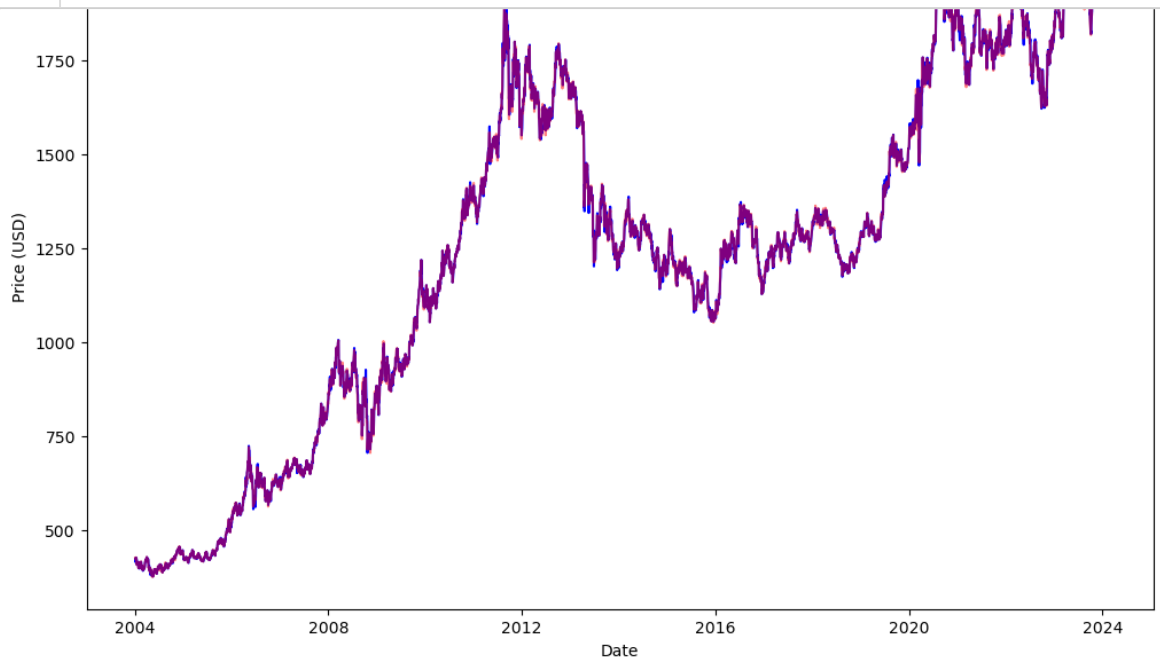
```



```
In [13]: 1 # Check Adj Close Price with Close Price difference
2 plt.figure(figsize=(12, 8))
3
4 plt.plot(goldDF['Date'], goldDF['Adj Close'], label='Adjusted Close Price')
5 plt.plot(goldDF['Date'], goldDF['Close'], label='Close Price', linestyle='dashed')
6
7 plt.legend()
8 plt.title('Adjusted Close Price vs. Closed Market Price')
9 plt.xlabel('Date')
10 plt.ylabel('Price (USD)')
11
12 plt.show()
```

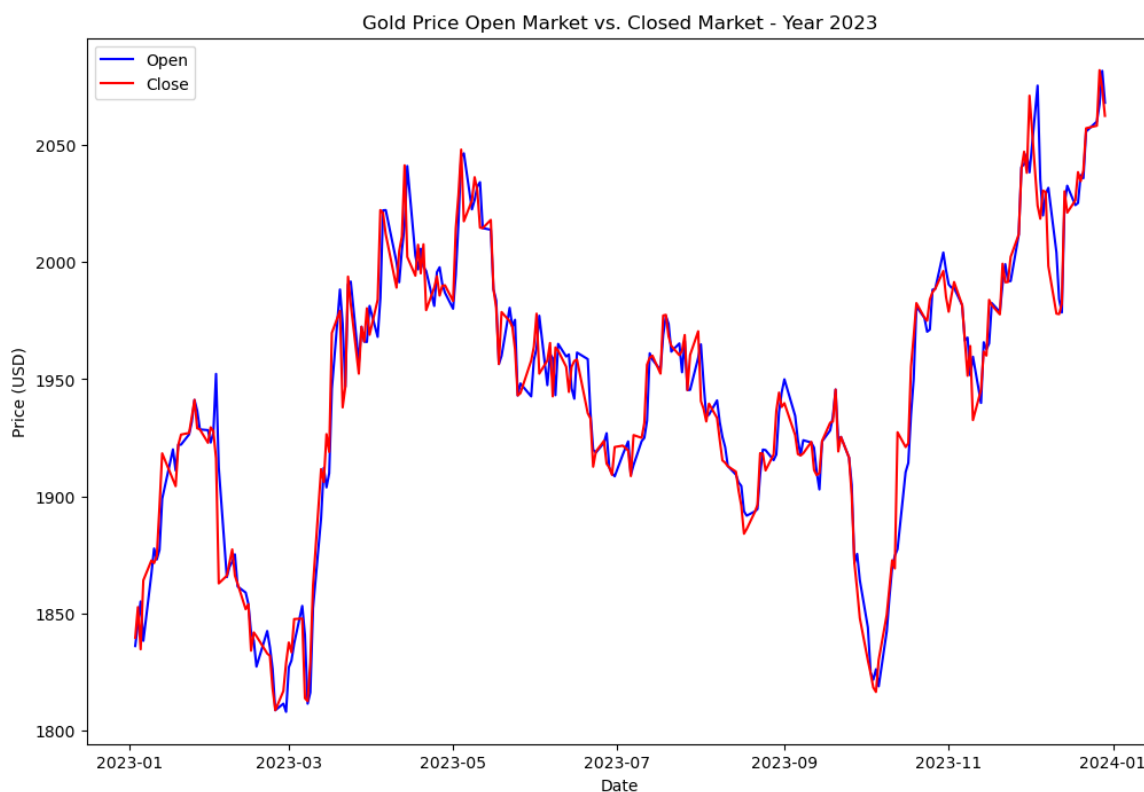


```
In [14]: 1 # Check Close Price with Open Price difference
2 plt.figure(figsize=(12, 8))
3
4 plt.plot(goldDF['Date'], goldDF['Open'], label='Open', linestyle='solid', color='blue')
5 plt.plot(goldDF['Date'], goldDF['Close'], label='Close', linestyle='solid', color='red')
6
7 plt.legend()
8 plt.title('Gold Price Open Market vs. Closed Market')
9 plt.xlabel('Date')
10 plt.ylabel('Price (USD)')
11
12 plt.show()
```



In [15]:

```
1 # Show Year 2023 plot
2 year2023 = goldDF[goldDF['Date'].dt.year == 2023]
3
4 plt.figure(figsize=(12, 8))
5
6 plt.plot(year2023['Date'], year2023['Open'], label='Open', linestyle='solid', color='blue')
7 plt.plot(year2023['Date'], year2023['Close'], label='Close', linestyle='solid', color='red')
8
9 plt.legend()
10 plt.title('Gold Price Open Market vs. Closed Market - Year 2023')
11 plt.xlabel('Date')
12 plt.ylabel('Price (USD)')
13
14 plt.show()
```




```

In [16]: 1 import mplfinance as mpf
          2
          3 # Show the plot use Candle Chart
          4 Fdf = goldDF.copy()
          5 Fdf.set_index('Date', inplace=True)
          6
          7 dec_2023 = Fdf.loc['2023-01-01':'2023-12-31']
          8
          9 mpf.plot(dec_2023, type='candle', mav=(3, 6, 9), figratio=(12, 8),
         10         title='Candle Chart 2023', show_nontrading=True)
         11
         12 mpf.show()

```

Candle Chart 2023

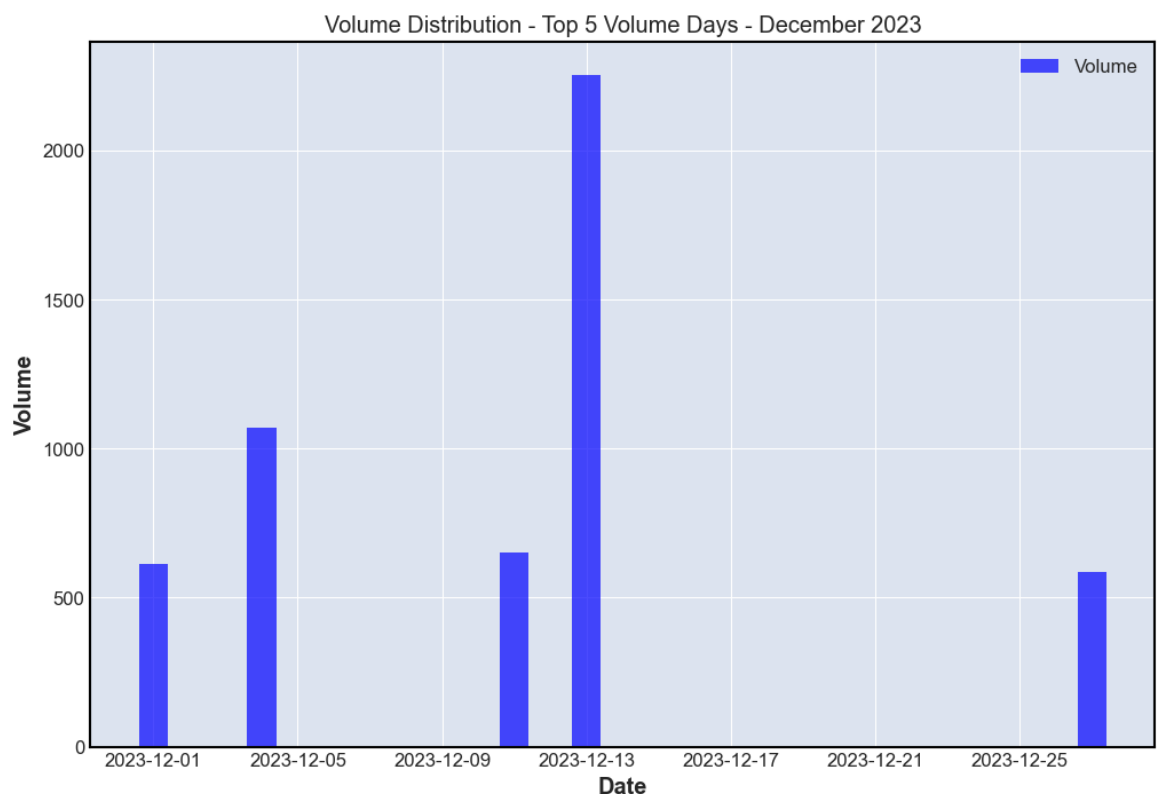


```
In [17]: 1 # Find the Top 5 volume at December 2023
2 goldDF['Date'] = pd.to_datetime(goldDF['Date'])
3
4 dec_2023_data = goldDF[(goldDF['Date'].dt.year == 2023) & (goldDF['Date'].dt.month == 12)]
5
6 top_5_volume_dec_2023 = dec_2023_data.sort_values(by='Volume', ascending=False)
7
8 print(top_5_volume_dec_2023)
```

	Date	Open	High	Low	Close
5012	2023-12-13	1978.500000	2024.800049	1975.000000	1982.300049
5005	2023-12-04	2075.300049	2130.199951	2021.000000	2024.099976
5010	2023-12-11	2004.099976	2004.199951	1977.199951	1978.000000
5004	2023-12-01	2038.300049	2073.199951	2036.000000	2071.000000
5021	2023-12-27	2067.300049	2081.899902	2064.800049	2081.899902

	Adj Close	Volume
5012	1982.300049	2252
5005	2024.099976	1071
5010	1978.000000	651
5004	2071.000000	614
5021	2081.899902	586

```
In [18]: 1 # Plotting the Top 5 Volume
2 plt.figure(figsize=(12, 8))
3 plt.bar(top_5_volume_dec_2023['Date'], top_5_volume_dec_2023['Volume'])
4
5 plt.legend(['Volume'])
6 plt.title('Volume Distribution - Top 5 Volume Days - December 2023')
7 plt.xlabel('Date')
8 plt.ylabel('Volume')
9
10 plt.show()
```



2023-12-13 - CPI report The U.S. CPI increased by 3.1% in November, and the market expects the Federal Reserve to continue to push interest rates higher on Wednesday. This report is bullish for gold, so traders will choose to enter the market at this time.

2023-12-22 - GDP report annualized growth rate is 4.9%, lower than the previous 5.2. This report is bullish for gold, so traders will choose to enter the market at this time.

The main reasons why gold rises and the US dollar falls

- Economic Uncertainty
- Inflation Hedge
- Currency Depreciation

Model Training and Validation

In [19]:

```

1  from sklearn.model_selection import train_test_split
2  from sklearn.preprocessing import StandardScaler, MinMaxScaler
3  from sklearn.ensemble import RandomForestClassifier, GradientBoos
4  from sklearn.linear_model import LogisticRegression
5  from sklearn.svm import SVC
6  from sklearn.metrics import accuracy_score
7  from keras.models import Sequential, Model
8  from keras.layers import LSTM, Dense, Dropout, Input
9  from keras.optimizers import Nadam
10 from sklearn.metrics import mean_absolute_percentage_error
11
12 goldDF['Daily_Return'] = goldDF['Close'].pct_change()
13
14 goldDF['Price_Up'] = (goldDF['Daily_Return'] > 0).astype(int)
15
16 features = ['Open', 'High', 'Low', 'Volume', 'Close']
17 target = 'Price_Up'
18 X = goldDF[features]
19 y = goldDF[target]
20
21 X_train, X_test, y_train, y_test = train_test_split(X, y, test_si
22
23 # RandomForestClassifier
24 rf_classifier = RandomForestClassifier(random_state=42)
25 rf_classifier.fit(X_train, y_train)
26 rf_predictions = rf_classifier.predict(X_test)
27 rf_accuracy = accuracy_score(y_test, rf_predictions)
28
29 # Support Vector Machine (SVM)
30 svm_classifier = SVC(random_state=42)
31 svm_classifier.fit(X_train, y_train)
32 svm_predictions = svm_classifier.predict(X_test)
33 svm_accuracy = accuracy_score(y_test, svm_predictions)
34
35 # GradientBoostingClassifier
36 gb_classifier = GradientBoostingClassifier(random_state=42)
37 gb_classifier.fit(X_train, y_train)
38 gb_predictions = gb_classifier.predict(X_test)
39 gb_accuracy = accuracy_score(y_test, gb_predictions)
40
41 # Logistic Regression
42 logreg_classifier = LogisticRegression(random_state=42)
43 logreg_classifier.fit(X_train, y_train)
44 logreg_predictions = logreg_classifier.predict(X_test)
45 logreg_accuracy = accuracy_score(y_test, logreg_predictions)
46
47 # Feature Scaling for LSTM
48 scaler = MinMaxScaler()
49 scaler.fit(goldDF.Close.values.reshape(-1,1))
50
51 test_size = 365
52 test_data = goldDF[-test_size:]
53
54 window_size = 60
55
56 def prepare_lstm_data(data, window_size):
57     X, y = [], []
58     for i in range(window_size, len(data)):
59         X.append(data[i - window_size:i, 0])
60         y.append(data[i, 0])
61     return np.array(X), np.array(y)

```

```

62
63 train_data = goldDF['Close'][:-test_size]
64 train_data = scaler.transform(train_data.values.reshape(-1, 1))
65 X_train, y_train = prepare_lstm_data(train_data, window_size)
66
67 test_data = goldDF['Close'][-test_size - window_size:]
68 test_data = scaler.transform(test_data.values.reshape(-1, 1))
69 X_test, y_test = prepare_lstm_data(test_data, window_size)
70
71 X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1]
72 X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1)
73 y_train = np.reshape(y_train, (-1, 1))
74 y_test = np.reshape(y_test, (-1, 1))
75
76 def define_model():
77     model = Sequential()
78     model.add(LSTM(units=64, return_sequences=True, input_shape=(
79     model.add(Dropout(0.2))
80     model.add(LSTM(units=64, return_sequences=True))
81     model.add(Dropout(0.2))
82     model.add(LSTM(units=64))
83     model.add(Dropout(0.2))
84     model.add(Dense(32, activation='softmax'))
85     model.add(Dense(1))
86
87     model.compile(loss='mean_squared_error', optimizer=Nadam())
88     model.summary()
89
90     return model
91
92 model = define_model()
93 history = model.fit(X_train, y_train, epochs=150, batch_size=32,
94 y_pred = model.predict(X_test)
95
96 MAPE = mean_absolute_percentage_error(y_test, y_pred)
97 lstm_accuracy = 1 - MAPE
98
99 print(f"Random Forest Accuracy: {rf_accuracy:.2%}")
100 print(f"SVM Accuracy: {svm_accuracy:.2%}")
101 print(f"Gradient Boosting Accuracy: {gb_accuracy:.2%}")
102 print(f"Logistic Regression Accuracy: {logreg_accuracy:.2%}")
103 print(f'LSTM model Accuracy: {lstm_accuracy:.2%}')

```

WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Nadam` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at `tf.keras.optimizers.legacy.Nadam`.

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 64)	16896
dropout (Dropout)	(None, 60, 64)	0
lstm_1 (LSTM)	(None, 60, 64)	33024
dropout_1 (Dropout)	(None, 60, 64)	0
lstm_2 (LSTM)	(None, 64)	33024
dropout_2 (Dropout)	(None, 64)	0
dense (Dense)	(None, 32)	2080
dense_1 (Dense)	(None, 1)	33

```

=====
Total params: 85057 (332.25 KB)
Trainable params: 85057 (332.25 KB)
Non-trainable params: 0 (0.00 Byte)
=====

```

```

Epoch 1/150
130/130 [=====] - 9s 48ms/step - loss: 0.06
87 - val_loss: 0.1403
Epoch 2/150
130/130 [=====] - 6s 46ms/step - loss: 0.00
99 - val_loss: 0.0584
Epoch 3/150
130/130 [=====] - 6s 47ms/step - loss: 0.00
41 - val_loss: 0.0297
Epoch 4/150
130/130 [=====] - 6s 47ms/step - loss: 0.00
21 - val_loss: 0.0165
Epoch 5/150
130/130 [=====] - 6s 47ms/step - loss: 0.00
14 - val_loss: 0.0104
Epoch 6/150
130/130 [=====] - 6s 47ms/step - loss: 0.00
12 - val_loss: 0.0072
Epoch 7/150
130/130 [=====] - 6s 48ms/step - loss: 9.93
34e-04 - val_loss: 0.0051
Epoch 8/150
130/130 [=====] - 6s 48ms/step - loss: 8.66
94e-04 - val_loss: 0.0037
Epoch 9/150
130/130 [=====] - 6s 48ms/step - loss: 8.14
08e-04 - val_loss: 0.0030
Epoch 10/150
130/130 [=====] - 6s 47ms/step - loss: 7.99
01e-04 - val_loss: 0.0025
Epoch 11/150
130/130 [=====] - 6s 47ms/step - loss: 7.20
77e-04 - val_loss: 0.0019
Epoch 12/150
130/130 [=====] - 6s 47ms/step - loss: 6.80
42e-04 - val_loss: 0.0029

```

```
Epoch 13/150
130/130 [=====] - 6s 47ms/step - loss: 6.09
63e-04 - val_loss: 0.0014
Epoch 14/150
130/130 [=====] - 6s 48ms/step - loss: 5.80
43e-04 - val_loss: 9.6973e-04
Epoch 15/150
130/130 [=====] - 6s 48ms/step - loss: 5.67
25e-04 - val_loss: 8.0587e-04
Epoch 16/150
130/130 [=====] - 6s 48ms/step - loss: 5.31
61e-04 - val_loss: 7.9941e-04
Epoch 17/150
130/130 [=====] - 6s 48ms/step - loss: 4.75
89e-04 - val_loss: 9.7697e-04
Epoch 18/150
130/130 [=====] - 6s 49ms/step - loss: 4.98
34e-04 - val_loss: 5.8434e-04
Epoch 19/150
130/130 [=====] - 6s 48ms/step - loss: 4.78
89e-04 - val_loss: 9.9430e-04
Epoch 20/150
130/130 [=====] - 6s 49ms/step - loss: 4.50
72e-04 - val_loss: 6.8833e-04
Epoch 21/150
130/130 [=====] - 6s 49ms/step - loss: 4.19
49e-04 - val_loss: 0.0014
Epoch 22/150
130/130 [=====] - 6s 49ms/step - loss: 4.29
78e-04 - val_loss: 8.5701e-04
Epoch 23/150
130/130 [=====] - 6s 49ms/step - loss: 4.11
54e-04 - val_loss: 8.7976e-04
Epoch 24/150
130/130 [=====] - 7s 51ms/step - loss: 3.96
71e-04 - val_loss: 3.8765e-04
Epoch 25/150
130/130 [=====] - 7s 51ms/step - loss: 3.77
12e-04 - val_loss: 8.9913e-04
Epoch 26/150
130/130 [=====] - 7s 51ms/step - loss: 3.80
16e-04 - val_loss: 6.0120e-04
Epoch 27/150
130/130 [=====] - 7s 52ms/step - loss: 3.55
81e-04 - val_loss: 0.0013
Epoch 28/150
130/130 [=====] - 7s 53ms/step - loss: 3.55
31e-04 - val_loss: 0.0019
Epoch 29/150
130/130 [=====] - 7s 51ms/step - loss: 3.25
08e-04 - val_loss: 6.9989e-04
Epoch 30/150
130/130 [=====] - 7s 51ms/step - loss: 3.25
65e-04 - val_loss: 5.3913e-04
Epoch 31/150
130/130 [=====] - 7s 53ms/step - loss: 3.04
25e-04 - val_loss: 6.4939e-04
Epoch 32/150
130/130 [=====] - 7s 53ms/step - loss: 3.18
34e-04 - val_loss: 0.0058
Epoch 33/150
```



```
130/130 [=====] - 7s 53ms/step - loss: 3.14
28e-04 - val_loss: 4.9159e-04
Epoch 34/150
130/130 [=====] - 7s 54ms/step - loss: 2.87
75e-04 - val_loss: 0.0033
Epoch 35/150
130/130 [=====] - 7s 53ms/step - loss: 2.81
36e-04 - val_loss: 3.2585e-04
Epoch 36/150
130/130 [=====] - 7s 56ms/step - loss: 2.76
64e-04 - val_loss: 0.0011
Epoch 37/150
130/130 [=====] - 7s 55ms/step - loss: 2.65
96e-04 - val_loss: 3.5432e-04
Epoch 38/150
130/130 [=====] - 7s 55ms/step - loss: 2.59
08e-04 - val_loss: 0.0012
Epoch 39/150
130/130 [=====] - 7s 55ms/step - loss: 2.54
65e-04 - val_loss: 0.0011
Epoch 40/150
130/130 [=====] - 7s 55ms/step - loss: 2.36
42e-04 - val_loss: 3.0848e-04
Epoch 41/150
130/130 [=====] - 7s 55ms/step - loss: 2.47
09e-04 - val_loss: 8.8270e-04
Epoch 42/150
130/130 [=====] - 7s 56ms/step - loss: 2.47
71e-04 - val_loss: 8.5205e-04
Epoch 43/150
130/130 [=====] - 7s 56ms/step - loss: 2.43
80e-04 - val_loss: 4.3493e-04
Epoch 44/150
130/130 [=====] - 7s 57ms/step - loss: 2.13
39e-04 - val_loss: 9.8199e-04
Epoch 45/150
130/130 [=====] - 7s 55ms/step - loss: 2.20
21e-04 - val_loss: 3.7605e-04
Epoch 46/150
130/130 [=====] - 7s 55ms/step - loss: 2.10
67e-04 - val_loss: 3.1032e-04
Epoch 47/150
130/130 [=====] - 7s 57ms/step - loss: 2.06
33e-04 - val_loss: 4.9096e-04
Epoch 48/150
130/130 [=====] - 7s 52ms/step - loss: 2.14
60e-04 - val_loss: 2.9713e-04
Epoch 49/150
130/130 [=====] - 7s 53ms/step - loss: 2.16
38e-04 - val_loss: 2.3370e-04
Epoch 50/150
130/130 [=====] - 7s 53ms/step - loss: 2.02
93e-04 - val_loss: 2.0971e-04
Epoch 51/150
130/130 [=====] - 7s 53ms/step - loss: 1.97
28e-04 - val_loss: 3.8455e-04
Epoch 52/150
130/130 [=====] - 7s 55ms/step - loss: 1.98
11e-04 - val_loss: 3.3287e-04
Epoch 53/150
130/130 [=====] - 7s 54ms/step - loss: 1.97
```

```
19e-04 - val_loss: 4.3932e-04
Epoch 54/150
130/130 [=====] - 7s 55ms/step - loss: 1.92
20e-04 - val_loss: 3.1269e-04
Epoch 55/150
130/130 [=====] - 7s 54ms/step - loss: 1.83
41e-04 - val_loss: 4.1792e-04
Epoch 56/150
130/130 [=====] - 7s 55ms/step - loss: 1.85
36e-04 - val_loss: 2.5792e-04
Epoch 57/150
130/130 [=====] - 7s 55ms/step - loss: 1.77
90e-04 - val_loss: 3.6777e-04
Epoch 58/150
130/130 [=====] - 7s 56ms/step - loss: 1.77
57e-04 - val_loss: 4.2625e-04
Epoch 59/150
130/130 [=====] - 7s 55ms/step - loss: 1.68
74e-04 - val_loss: 3.2402e-04
Epoch 60/150
130/130 [=====] - 7s 56ms/step - loss: 1.71
91e-04 - val_loss: 2.9569e-04
Epoch 61/150
130/130 [=====] - 7s 55ms/step - loss: 1.81
48e-04 - val_loss: 3.5007e-04
Epoch 62/150
```

```
130/130 [=====] - 7s 54ms/step - loss: 1.78
03e-04 - val_loss: 2.9365e-04
Epoch 63/150
130/130 [=====] - 7s 54ms/step - loss: 1.69
99e-04 - val_loss: 2.3240e-04
Epoch 64/150
130/130 [=====] - 6s 50ms/step - loss: 1.74
52e-04 - val_loss: 2.8314e-04
Epoch 65/150
130/130 [=====] - 7s 50ms/step - loss: 1.67
21e-04 - val_loss: 5.7346e-04
Epoch 66/150
130/130 [=====] - 6s 49ms/step - loss: 1.67
20e-04 - val_loss: 1.9001e-04
Epoch 67/150
130/130 [=====] - 6s 50ms/step - loss: 1.61
77e-04 - val_loss: 2.4671e-04
Epoch 68/150
130/130 [=====] - 7s 51ms/step - loss: 1.62
54e-04 - val_loss: 2.2924e-04
Epoch 69/150
130/130 [=====] - 7s 51ms/step - loss: 1.63
60e-04 - val_loss: 0.0020
Epoch 70/150
130/130 [=====] - 7s 51ms/step - loss: 1.63
88e-04 - val_loss: 3.7957e-04
Epoch 71/150
130/130 [=====] - 6s 50ms/step - loss: 1.61
52e-04 - val_loss: 3.7433e-04
Epoch 72/150
130/130 [=====] - 6s 50ms/step - loss: 1.51
04e-04 - val_loss: 2.6918e-04
Epoch 73/150
130/130 [=====] - 7s 50ms/step - loss: 1.62
53e-04 - val_loss: 2.5127e-04
Epoch 74/150
130/130 [=====] - 6s 50ms/step - loss: 1.47
83e-04 - val_loss: 1.7861e-04
Epoch 75/150
130/130 [=====] - 7s 50ms/step - loss: 1.52
62e-04 - val_loss: 2.3398e-04
Epoch 76/150
130/130 [=====] - 7s 51ms/step - loss: 1.57
99e-04 - val_loss: 2.3907e-04
Epoch 77/150
130/130 [=====] - 7s 51ms/step - loss: 1.52
88e-04 - val_loss: 7.0411e-04
Epoch 78/150
130/130 [=====] - 7s 52ms/step - loss: 1.53
56e-04 - val_loss: 5.7625e-04
Epoch 79/150
130/130 [=====] - 7s 53ms/step - loss: 1.45
55e-04 - val_loss: 0.0011
Epoch 80/150
130/130 [=====] - 7s 52ms/step - loss: 1.52
66e-04 - val_loss: 2.5387e-04
Epoch 81/150
130/130 [=====] - 7s 51ms/step - loss: 1.53
59e-04 - val_loss: 3.6928e-04
Epoch 82/150
130/130 [=====] - 7s 52ms/step - loss: 1.49
```

```
63e-04 - val_loss: 2.2111e-04
Epoch 83/150
130/130 [=====] - 7s 52ms/step - loss: 1.43
32e-04 - val_loss: 7.7345e-04
Epoch 84/150
130/130 [=====] - 7s 52ms/step - loss: 1.41
79e-04 - val_loss: 2.1163e-04
Epoch 85/150
130/130 [=====] - 7s 55ms/step - loss: 1.49
57e-04 - val_loss: 2.1290e-04
Epoch 86/150
130/130 [=====] - 7s 53ms/step - loss: 1.38
96e-04 - val_loss: 2.5912e-04
Epoch 87/150
130/130 [=====] - 7s 54ms/step - loss: 1.43
64e-04 - val_loss: 2.7561e-04
Epoch 88/150
130/130 [=====] - 7s 53ms/step - loss: 1.39
98e-04 - val_loss: 1.7825e-04
Epoch 89/150
130/130 [=====] - 7s 54ms/step - loss: 1.37
00e-04 - val_loss: 1.9892e-04
Epoch 90/150
130/130 [=====] - 7s 53ms/step - loss: 1.39
66e-04 - val_loss: 4.1500e-04
Epoch 91/150
130/130 [=====] - 7s 53ms/step - loss: 1.34
09e-04 - val_loss: 4.8989e-04
Epoch 92/150
130/130 [=====] - 7s 53ms/step - loss: 1.41
24e-04 - val_loss: 2.5452e-04
Epoch 93/150
130/130 [=====] - 7s 55ms/step - loss: 1.36
36e-04 - val_loss: 4.4774e-04
Epoch 94/150
130/130 [=====] - 7s 57ms/step - loss: 1.38
97e-04 - val_loss: 4.6326e-04
Epoch 95/150
130/130 [=====] - 7s 55ms/step - loss: 1.42
39e-04 - val_loss: 1.6627e-04
Epoch 96/150
130/130 [=====] - 7s 54ms/step - loss: 1.40
89e-04 - val_loss: 2.7423e-04
Epoch 97/150
130/130 [=====] - 8s 58ms/step - loss: 1.33
42e-04 - val_loss: 6.4664e-04
Epoch 98/150
130/130 [=====] - 7s 57ms/step - loss: 1.39
87e-04 - val_loss: 1.8653e-04
Epoch 99/150
130/130 [=====] - 7s 57ms/step - loss: 1.33
33e-04 - val_loss: 3.9297e-04
Epoch 100/150
130/130 [=====] - 7s 56ms/step - loss: 1.34
52e-04 - val_loss: 1.9901e-04
Epoch 101/150
130/130 [=====] - 7s 56ms/step - loss: 1.35
28e-04 - val_loss: 2.7606e-04
Epoch 102/150
130/130 [=====] - 7s 54ms/step - loss: 1.29
05e-04 - val_loss: 3.5310e-04
```

```
Epoch 103/150
130/130 [=====] - 7s 56ms/step - loss: 1.32
22e-04 - val_loss: 2.6192e-04
Epoch 104/150
130/130 [=====] - 7s 55ms/step - loss: 1.32
21e-04 - val_loss: 3.0489e-04
Epoch 105/150
130/130 [=====] - 7s 56ms/step - loss: 1.31
44e-04 - val_loss: 2.1116e-04
Epoch 106/150
130/130 [=====] - 8s 59ms/step - loss: 1.26
17e-04 - val_loss: 2.5846e-04
Epoch 107/150
130/130 [=====] - 7s 57ms/step - loss: 1.35
19e-04 - val_loss: 2.2094e-04
Epoch 108/150
130/130 [=====] - 7s 56ms/step - loss: 1.36
75e-04 - val_loss: 3.8278e-04
Epoch 109/150
130/130 [=====] - 7s 56ms/step - loss: 1.24
22e-04 - val_loss: 4.8913e-04
Epoch 110/150
130/130 [=====] - 8s 58ms/step - loss: 1.30
51e-04 - val_loss: 2.4594e-04
Epoch 111/150
130/130 [=====] - 7s 56ms/step - loss: 1.27
72e-04 - val_loss: 5.7276e-04
Epoch 112/150
130/130 [=====] - 7s 57ms/step - loss: 1.26
83e-04 - val_loss: 2.0813e-04
Epoch 113/150
130/130 [=====] - 7s 56ms/step - loss: 1.27
31e-04 - val_loss: 2.7574e-04
Epoch 114/150
130/130 [=====] - 7s 55ms/step - loss: 1.21
81e-04 - val_loss: 1.6884e-04
Epoch 115/150
130/130 [=====] - 7s 55ms/step - loss: 1.18
90e-04 - val_loss: 2.8837e-04
Epoch 116/150
130/130 [=====] - 7s 57ms/step - loss: 1.22
31e-04 - val_loss: 2.7094e-04
Epoch 117/150
130/130 [=====] - 8s 59ms/step - loss: 1.42
31e-04 - val_loss: 1.9579e-04
Epoch 118/150
130/130 [=====] - 8s 59ms/step - loss: 1.29
52e-04 - val_loss: 2.3072e-04
Epoch 119/150
130/130 [=====] - 7s 58ms/step - loss: 1.27
69e-04 - val_loss: 2.1149e-04
Epoch 120/150
130/130 [=====] - 8s 60ms/step - loss: 1.21
47e-04 - val_loss: 4.5995e-04
Epoch 121/150
130/130 [=====] - 7s 56ms/step - loss: 1.24
69e-04 - val_loss: 6.2655e-04
Epoch 122/150
130/130 [=====] - 8s 59ms/step - loss: 1.28
85e-04 - val_loss: 2.8194e-04
Epoch 123/150
```

```
130/130 [=====] - 7s 57ms/step - loss: 1.25
93e-04 - val_loss: 3.6366e-04
Epoch 124/150
130/130 [=====] - 7s 53ms/step - loss: 1.23
81e-04 - val_loss: 4.4767e-04
Epoch 125/150
130/130 [=====] - 7s 55ms/step - loss: 1.21
79e-04 - val_loss: 2.6016e-04
Epoch 126/150
130/130 [=====] - 7s 53ms/step - loss: 1.18
81e-04 - val_loss: 1.7591e-04
Epoch 127/150
130/130 [=====] - 7s 51ms/step - loss: 1.17
62e-04 - val_loss: 5.7084e-04
Epoch 128/150
130/130 [=====] - 7s 51ms/step - loss: 1.18
45e-04 - val_loss: 2.8367e-04
Epoch 129/150
130/130 [=====] - 7s 51ms/step - loss: 1.22
79e-04 - val_loss: 2.2399e-04
Epoch 130/150
130/130 [=====] - 7s 52ms/step - loss: 1.30
17e-04 - val_loss: 2.0285e-04
Epoch 131/150
130/130 [=====] - 7s 53ms/step - loss: 1.19
57e-04 - val_loss: 2.3243e-04
Epoch 132/150
130/130 [=====] - 6s 50ms/step - loss: 1.20
49e-04 - val_loss: 2.7375e-04
Epoch 133/150
130/130 [=====] - 7s 51ms/step - loss: 1.25
48e-04 - val_loss: 5.9574e-04
Epoch 134/150
130/130 [=====] - 7s 51ms/step - loss: 1.19
01e-04 - val_loss: 4.9511e-04
Epoch 135/150
```

```
130/130 [=====] - 7s 52ms/step - loss: 1.17
08e-04 - val_loss: 1.8648e-04
Epoch 136/150
130/130 [=====] - 7s 52ms/step - loss: 1.18
64e-04 - val_loss: 3.8469e-04
Epoch 137/150
130/130 [=====] - 7s 51ms/step - loss: 1.13
67e-04 - val_loss: 2.1262e-04
Epoch 138/150
130/130 [=====] - 7s 51ms/step - loss: 1.20
62e-04 - val_loss: 1.7391e-04
Epoch 139/150
130/130 [=====] - 7s 52ms/step - loss: 1.14
90e-04 - val_loss: 2.3241e-04
Epoch 140/150
130/130 [=====] - 7s 51ms/step - loss: 1.18
25e-04 - val_loss: 2.7959e-04
Epoch 141/150
130/130 [=====] - 7s 51ms/step - loss: 1.18
18e-04 - val_loss: 3.8640e-04
Epoch 142/150
130/130 [=====] - 7s 51ms/step - loss: 1.19
23e-04 - val_loss: 2.3734e-04
Epoch 143/150
130/130 [=====] - 7s 51ms/step - loss: 1.14
12e-04 - val_loss: 3.1466e-04
Epoch 144/150
130/130 [=====] - 7s 51ms/step - loss: 1.17
84e-04 - val_loss: 5.8081e-04
Epoch 145/150
130/130 [=====] - 7s 52ms/step - loss: 1.22
56e-04 - val_loss: 2.5801e-04
Epoch 146/150
130/130 [=====] - 7s 51ms/step - loss: 1.15
61e-04 - val_loss: 3.1902e-04
Epoch 147/150
130/130 [=====] - 7s 53ms/step - loss: 1.16
19e-04 - val_loss: 2.2802e-04
Epoch 148/150
130/130 [=====] - 7s 54ms/step - loss: 1.15
65e-04 - val_loss: 4.6153e-04
Epoch 149/150
130/130 [=====] - 7s 54ms/step - loss: 1.19
45e-04 - val_loss: 3.3898e-04
Epoch 150/150
130/130 [=====] - 7s 53ms/step - loss: 1.10
51e-04 - val_loss: 1.7987e-04
12/12 [=====] - 1s 12ms/step
Random Forest Accuracy: 66.27%
SVM Accuracy: 52.58%
Gradient Boosting Accuracy: 63.69%
Logistic Regression Accuracy: 78.87%
LSTM model Accuracy: 98.09%
```

```
In [20]: 1 # Save LSTM model
2 model.save('gold_price_prediction_model.h5')
3
4 print("Best Model saved successfully.")
```

Best Model saved successfully.

```
In [21]: 1 best_model = None
2 best_accuracy = 0.0
3
4 if rf_accuracy > best_accuracy:
5     best_accuracy = rf_accuracy
6     best_model = rf_classifier
7
8 if svm_accuracy > best_accuracy:
9     best_accuracy = svm_accuracy
10    best_model = svm_classifier
11
12 if gb_accuracy > best_accuracy:
13     best_accuracy = gb_accuracy
14     best_model = gb_classifier
15
16 if logreg_accuracy > best_accuracy:
17     best_accuracy = logreg_accuracy
18     best_model = logreg_classifier
19
20 if lstm_accuracy > best_accuracy:
21     best_accuracy = lstm_accuracy
22     best_model = model
23
24 print(f"The best model is {type(best_model).__name__} with an accu
```

The best model is Sequential with an accuracy of 98.09%

In [25]:

```

1 import numpy as np
2 import pandas as pd
3 from datetime import datetime, timedelta
4 import yfinance as yf
5 from sklearn.preprocessing import MinMaxScaler
6 from tensorflow.keras.models import load_model
7 import matplotlib.pyplot as plt
8
9 # Define the calculate_rsi function
10 def calculate_rsi(data, window=14):
11     close_price = data['Close']
12     delta = close_price.diff()
13
14     gain = delta.where(delta > 0, 0)
15     loss = -delta.where(delta < 0, 0)
16
17     avg_gain = gain.rolling(window=window, min_periods=1).mean()
18     avg_loss = loss.rolling(window=window, min_periods=1).mean()
19
20     rs = avg_gain / avg_loss
21     rsi = 100 - (100 / (1 + rs))
22
23     return rsi
24
25 # Define the market_status function
26 def market_status(rsi_value):
27     if rsi_value > 70:
28         return 'Overbought'
29     elif rsi_value < 30:
30         return 'Oversold'
31     else:
32         return 'Neutral'
33
34
35 model = load_model('gold_price_prediction_model.h5')
36
37 input_date = pd.to_datetime(input("\nEnter the date to visualize
38
39 days_ranges = [180, 365]
40 days_before = max(days_ranges) // 2
41 days_after = days_before
42
43 window_size = 60
44 for days_range in days_ranges:
45     plot_start_date = input_date - pd.Timedelta(days=days_range //
46     plot_end_date = input_date + pd.Timedelta(days=days_range //
47
48     try:
49         plot_data = yf.download('GC=F', start=plot_start_date, en
50
51         if len(plot_data) >= window_size:
52             input_data = plot_data['Close'][-window_size:].values
53
54             scaler = MinMaxScaler()
55             scaler.fit(plot_data['Close'].values.reshape(-1, 1))
56
57             def predict_gold_price(input_data):
58                 input_data = scaler.transform(input_data.reshape(
59                 input_data = np.reshape(input_data, (1, window_si
60                 predicted_price = model.predict(input_data)
61                 predicted_price = scaler.inverse_transform(predic

```

```

62         return predicted_price[0, 0]
63
64     predictions = []
65     future_dates = [input_date + timedelta(days=i) for i
66                     for i in range(days_after + 1)]:
67         predictions.append(predict_gold_price(input_data))
68         input_data = np.append(input_data[1:], prediction)
69
70     last_day_difference = ((predictions[-1] - plot_data['
71                           plot_data['Close'].iloc[-1])) *
72
73     last_day_direction = 'Up' if last_day_difference > 0
74
75     last_day_date = plot_data.index[-1]
76
77     # Calculate close_price here
78     close_price = plot_data['Close'].iloc[-1]
79
80     print(f"The price is expected to go {last_day_directi
81     print(f"Predicted price on {last_day_date.strftime('%
82     print(f"Predicted price after {days_range} days on {f
83
84     plt.figure(figsize=(10, 6))
85
86     plt.subplot(2, 1, 1)
87     plt.plot(plot_data.index, plot_data['Close'], label='
88     plt.plot(future_dates, predictions, color='orange', l
89     plt.axvline(x=input_date, color='red', linestyle='--'
90
91     plt.scatter(input_date, predictions[0], color='green'
92     plt.text(input_date, predictions[0], f'USD {predictio
93             va='bottom', color='green')
94     plt.scatter(input_date, plot_data['Close'].iloc[-1],
95     plt.axvline(x=input_date, color='red', linestyle='-')
96     plt.text(input_date, close_price, f'USD {close_price:
97             va='bottom', color='red')
98
99     last_day_annotation = f'{future_dates[-1].strftime("%
100    plt.scatter(future_dates[-1], predictions[-1], color=
101    plt.text(future_dates[-1], predictions[-1], last_day_
102            va='bottom', color='purple')
103
104    plt.title(f'Gold Price Data Around {input_date.strfti
105    plt.xlabel('Date')
106    plt.ylabel('Gold Price')
107    plt.legend()
108    plt.grid(True)
109
110    # Plotting RSI
111    plt.subplot(2, 1, 2)
112    rsi_data = calculate_rsi(plot_data)
113    plt.plot(plot_data.index, rsi_data, label='RSI', line
114    plt.axhline(y=70, color='red', linestyle='--', label=
115    plt.axhline(y=30, color='green', linestyle='--', labe
116
117    # Add red vertical line for input date
118    plt.axvline(x=input_date, color='red', linestyle='-')
119
120    market_status_value = market_status(rsi_data.iloc[-1]
121    plt.title(f'Market Status: {market_status_value}')
122    plt.xlabel('Date')

```

```
123         plt.ylabel('RSI')
124         plt.legend()
125         plt.grid(True)
126
127         plt.tight_layout()
128         plt.show()
129
130     else:
131         print(f"Insufficient historical data for scaling in t
132
133     except Exception as e:
134         print(f"Failed to download data for the {days_range}-day
135
```

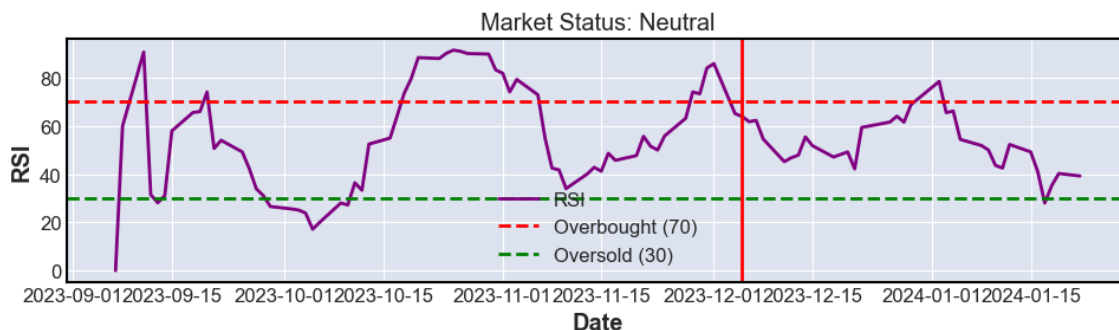
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Nadam` runs slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at `tf.keras.optimizers.legacy.Nadam`.

localhost:8889/notebooks/Desktop/Code/Forward School/Sem 3 (Python)/DS Project/Project DS(Stock Market Trends with Time Series Analysis using Yaho... 29/36

[illegible]

```
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```

The price is expected to go Down by 0.88%
 Predicted price on 2024-01-22: USD 2006.80
 Predicted price after 180 days on 2024-06-04 is USD 2024.70



[illegible]

```
1/1 [=====] - 0s 13ms/step
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The price is expected to go Down by 0.88%

Predicted price on 2024-01-22: USD 2006.80

Predicted price after 365 days on 2024-06-04 is USD 2024.60

