Problem statement:

This project aims to leverage a comprehensive dataset of daily gold prices spanning from January 19, 2014, to January 22, 2024, obtained from Nasdaq. The dataset encompasses key financial metrics for each trading day, including the opening and closing prices, trading volume, as well as the highest and lowest prices recorded during the day.

Reading gold stock data (avaliable at: https://www.kaggle.com/datasets/sahilwagh/gold-stock-prices)

Principle Aim:

The main goal of the project is to analyze daily gold prices over a ten-year period, using key financial metrics such as opening and closing prices, trading volume, and highest and lowest prices. This analysis aims to identify trends, patterns, and factors influencing gold prices, and develop predictive models for forecasting future gold prices.

```
# Data Loading
from google.colab import drive
import pandas as pd
drive.mount('/content/drive')
file_path = '/content/drive/My Drive/goldstock.csv'
df = pd.read_csv(file_path)
```

```
Mounted at /content/drive
```

```
df.head()
```

	Unnamed: 0	Date	Close	Volume	Open	High	Low
0	0	2024-01-19	2029.3	166078.0	2027.4	2041.9	2022.2
1	1	2024-01-18	2021.6	167013.0	2009.1	2025.6	2007.7
2	2	2024-01-17	2006.5	245194.0	2031.7	2036.1	2004.6
3	3	2024-01-16	2030.2	277995.0	2053.4	2062.8	2027.6
4	4	2024-01-12	2051.6	250946.0	2033.2	2067.3	2033.1

Next steps: Generate code with df View recommended plots

```
df.tail()
```

	Unnamed: 0	Date	Close	Volume	Open	High	Low
2506	2528	2014-01-28	1250.5	81426.0	1254.9	1261.9	1248.0
2507	2529	2014-01-27	1263.5	63419.0	1269.9	1280.1	1252.0
2508	2530	2014-01-24	1264.5	34998.0	1264.3	1273.2	1256.9
2509	2531	2014-01-23	1262.5	41697.0	1235.1	1267.1	1230.8

2510	2532	2014-01-22	1238.6	80262.0	1240.5	1243.5	1235.5

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2511 entries, 0 to 2510
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  2511 non-null   int64
 1   Date        2511 non-null   object
 2   Close       2511 non-null   float64
 3   Volume      2511 non-null   float64
 4   Open        2511 non-null   float64
 5   High        2511 non-null   float64
 6   Low         2511 non-null   float64
dtypes: float64(5), int64(1), object(1)
memory usage: 137.4+ KB
```

Features:

i. Date- A unique identifier for each trading day.

ii. Close- Closing price of gold on the respective date.

iii. Volume- Gold trading volume on the corresponding date.

iv. Open- Opening price of gold on the respective date.

v. High- The highest recorded price of gold during the trading day.

vi. Low- The lowest price recorded for gold in the trading day.

Target Variable:

** Close- Closing price of gold on the respective date.

```
df.shape
```

```
(2511, 7)
```

```
df.isnull().sum()
```

```
Unnamed: 0    0
Date          0
Close         0
Volume        0
Open          0
High          0
Low           0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

```
df.describe()
```

	Unnamed: 0	Close	Volume	Open	High	Low
count	2511.000000	2511.000000	2511.000000	2511.000000	2511.000000	2511.00000
mean	1260.792911	1498.726085	185970.770609	1498.725528	1508.451454	1488.86993
std	729.262879	298.824811	97600.769382	299.118187	301.262244	296.41770
min	0.000000	1049.600000	1.000000	1051.500000	1062.700000	1045.40000
25%	630.500000	1249.850000	126693.500000	1249.500000	1257.300000	1242.35000
50%	1259.000000	1332.800000	175421.000000	1334.000000	1342.400000	1326.60000
75%	1888.500000	1805.850000	234832.000000	1805.600000	1815.450000	1793.05000
max	2532.000000	2093.100000	787217.000000	2094.400000	2098.200000	2074.60000

```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
```

```
df = df.drop("Unnamed: 0", axis = 1)
df
```

	Date	Close	Volume	Open	High	Low
0	2024-01-19	2029.3	166078.0	2027.4	2041.9	2022.2
1	2024-01-18	2021.6	167013.0	2009.1	2025.6	2007.7
2	2024-01-17	2006.5	245194.0	2031.7	2036.1	2004.6
3	2024-01-16	2030.2	277995.0	2053.4	2062.8	2027.6
4	2024-01-12	2051.6	250946.0	2033.2	2067.3	2033.1
...	...	...	...	...	...	...
2506	2014-01-28	1250.5	81426.0	1254.9	1261.9	1248.0
2507	2014-01-27	1263.5	63419.0	1269.9	1280.1	1252.0
2508	2014-01-24	1264.5	34998.0	1264.3	1273.2	1256.9

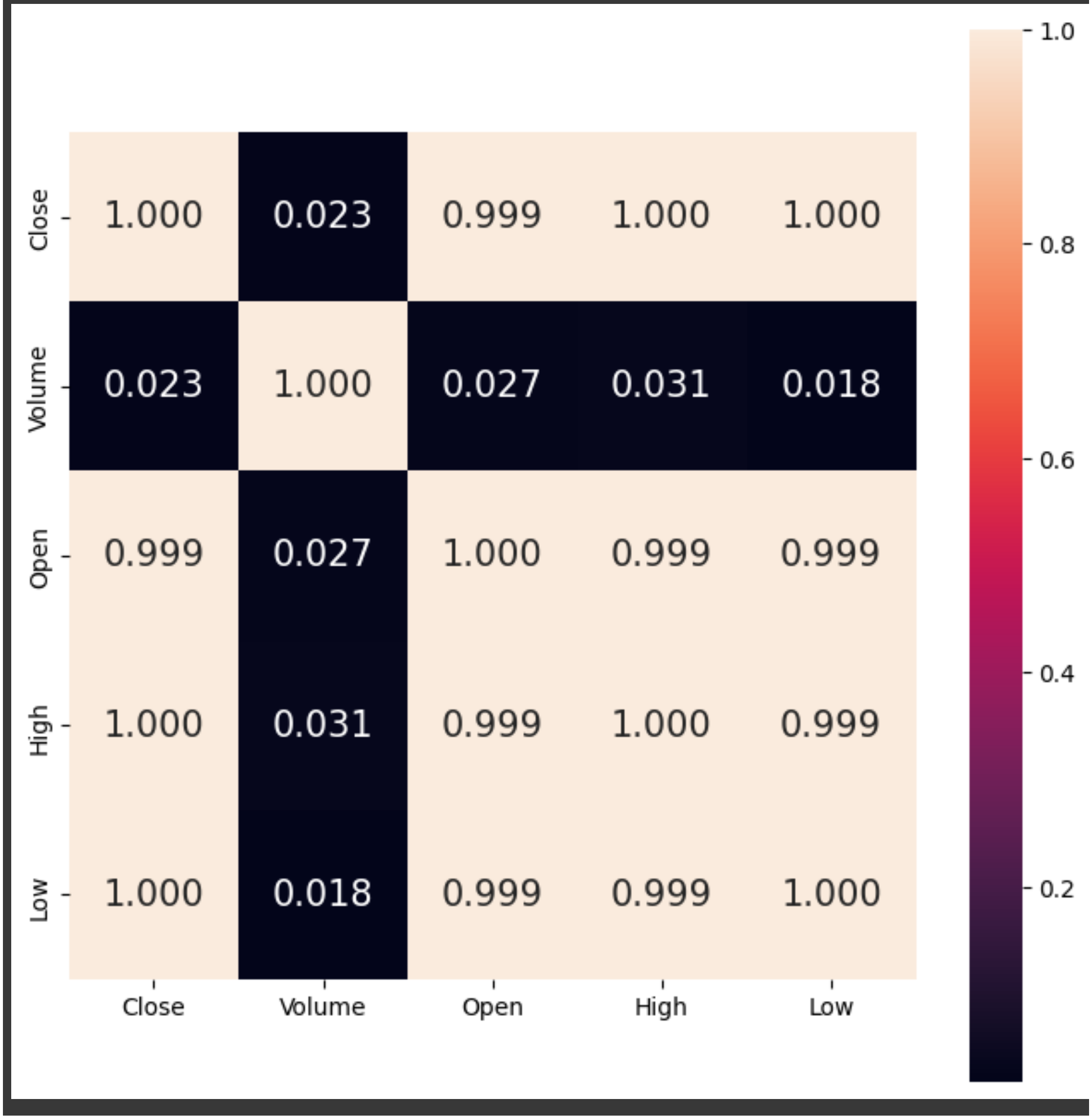
2509	2014-01-23	1262.5	41697.0	1235.1	1267.1	1230.8
2510	2014-01-22	1238.6	80262.0	1240.5	1243.5	1235.5

2511 rows × 6 columns

Next steps: Generate code with df View recommended plots

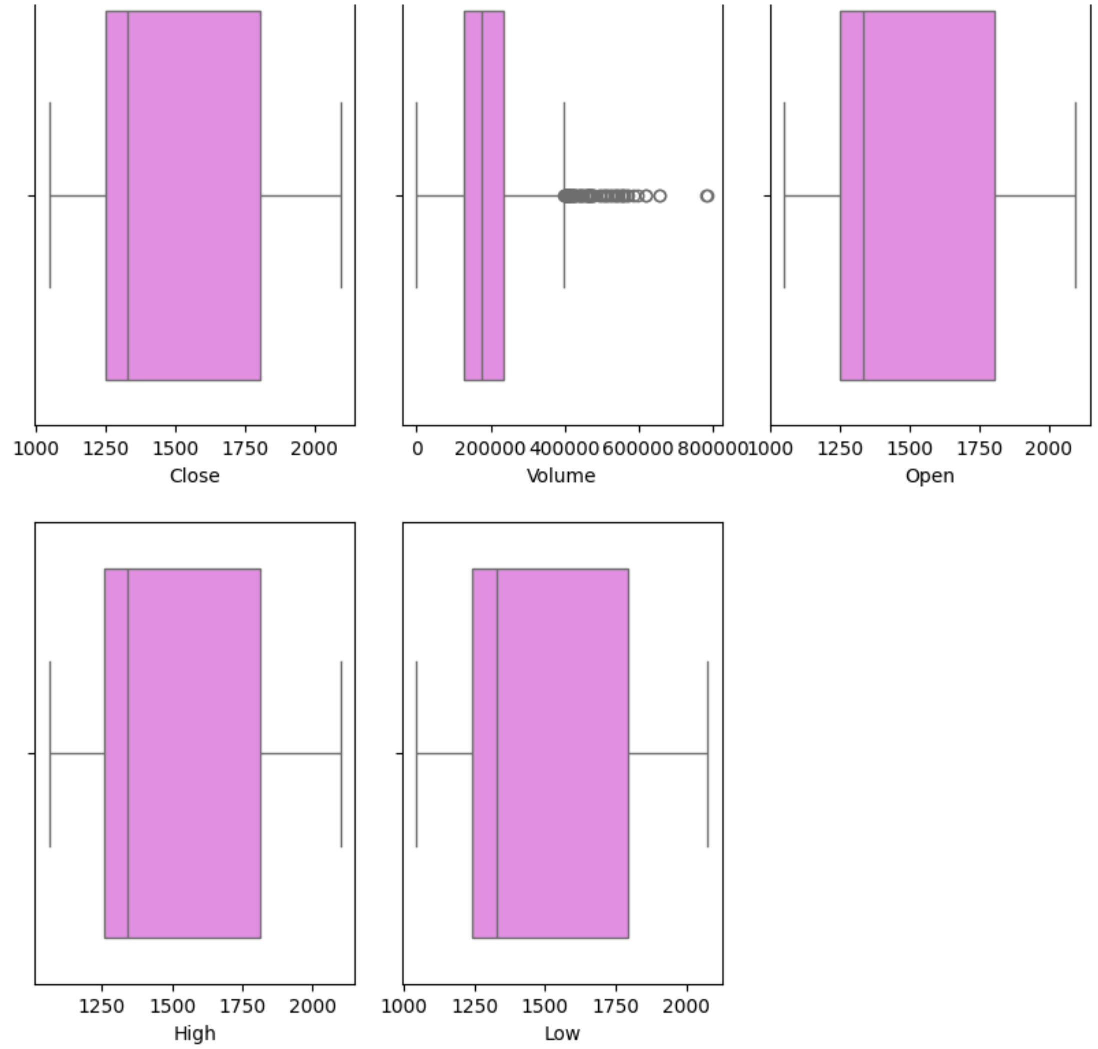
```
correlation = df.corr()
plt.figure(figsize = (8,8))
sns.heatmap(correlation, cbar=True, square=True, fmt='.3f',annot=True, annot_kw
```

<Axes: >



```
# Convert 'Date' column to datetime
df['Date'] = pd.to_datetime(df['Date'])

# Plot historical gold prices
plt.figure(figsize=(10, 6))
plt.plot(df['Date'], df['Close'], label='Gold Price')
plt.xlabel('Year')
plt.ylabel('Gold Price')
plt.title('Historical Gold Prices')
plt.legend()
plt.show()
```


```
fig = plt.figure(figsize=(8, 8))
temp = df.drop("Date", axis=1).columns.tolist()
for i, item in enumerate(temp):
    plt.subplot(2, 3, i+1)
    sns.boxplot(data=df, x=item, color='violet')

plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=2.0)
plt.show()
```

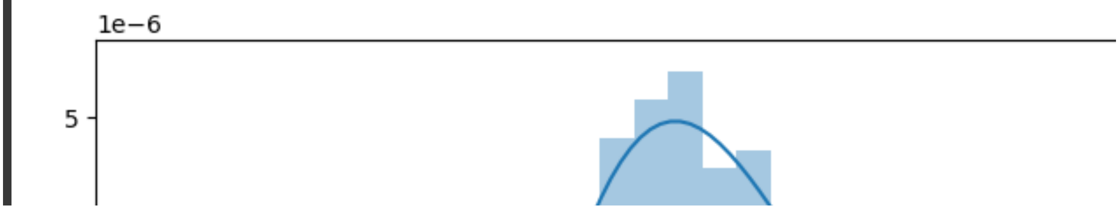


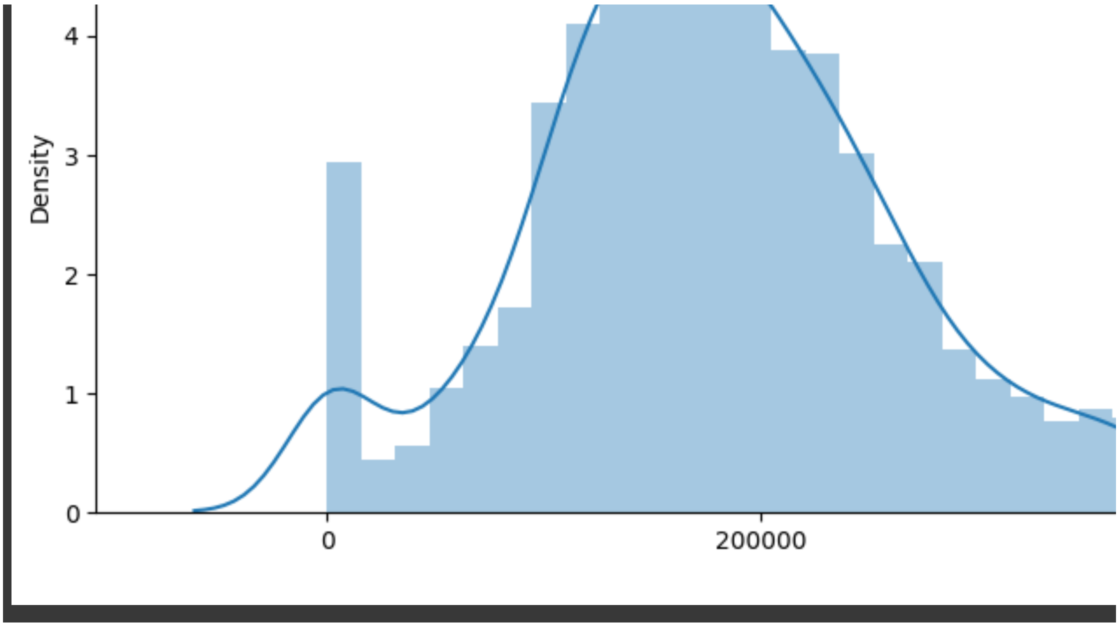

```
df['Volume'].skew()
```

    0.9184323957685832

```
plt.figure(figsize = (16,5))
sns.distplot(df['Volume'])
```

    <Axes: xlabel='Volume', ylabel='Density'>



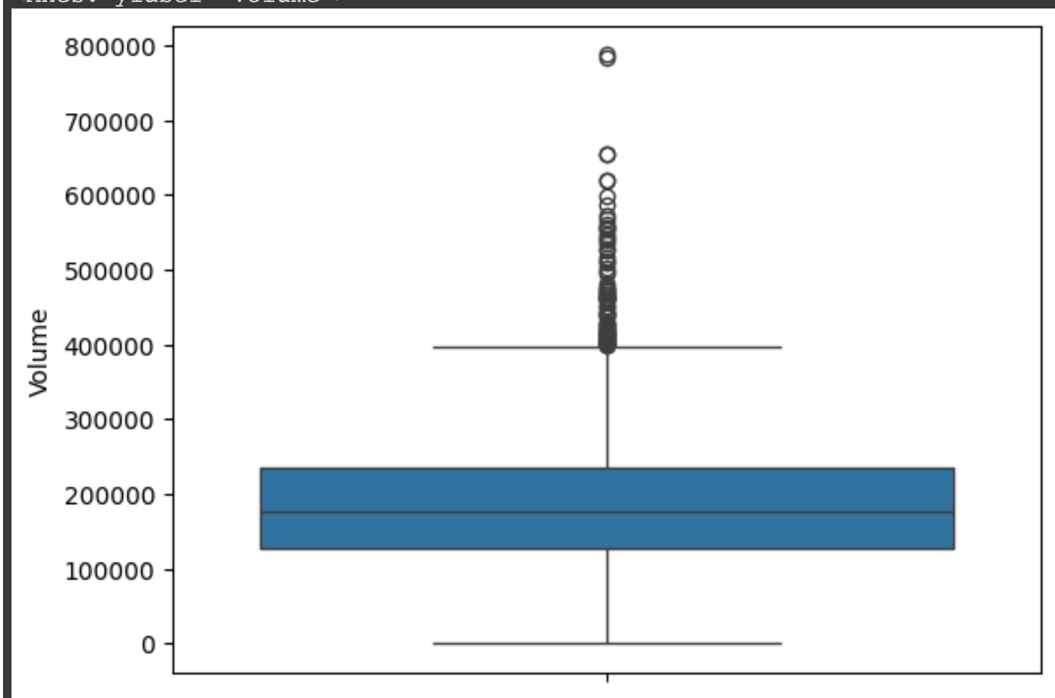



```
df['Volume'].describe()
```

```
count      2511.000000
mean     185970.770609
std       97600.769382
min           1.000000
25%      126693.500000
50%      175421.000000
75%      234832.000000
max      787217.000000
Name: Volume, dtype: float64
```

```
sns.boxplot(df['Volume'])
```

<Axes: ylabel='Volume'>



```
#finding the IQR # Calculate Q1 (25th percentile) and Q3 (75th percentile)

percentile25 = df['Volume'].quantile(0.25)
percentile75 = df['Volume'].quantile(0.75)
```

```
percentile75
```

```
234832.0
```

```
IQR = percentile75 - percentile25
IQR
```

```
108138.5
```

```
upperlimit = percentile75 + 1.5 *IQR
lowerlimit = percentile25 - 1.5 * IQR
print("Upperlimit : ", upperlimit)
print("lowerlimit : ", lowerlimit)
```

```
Upperlimit :  397039.75
lowerlimit :  -35514.25
```

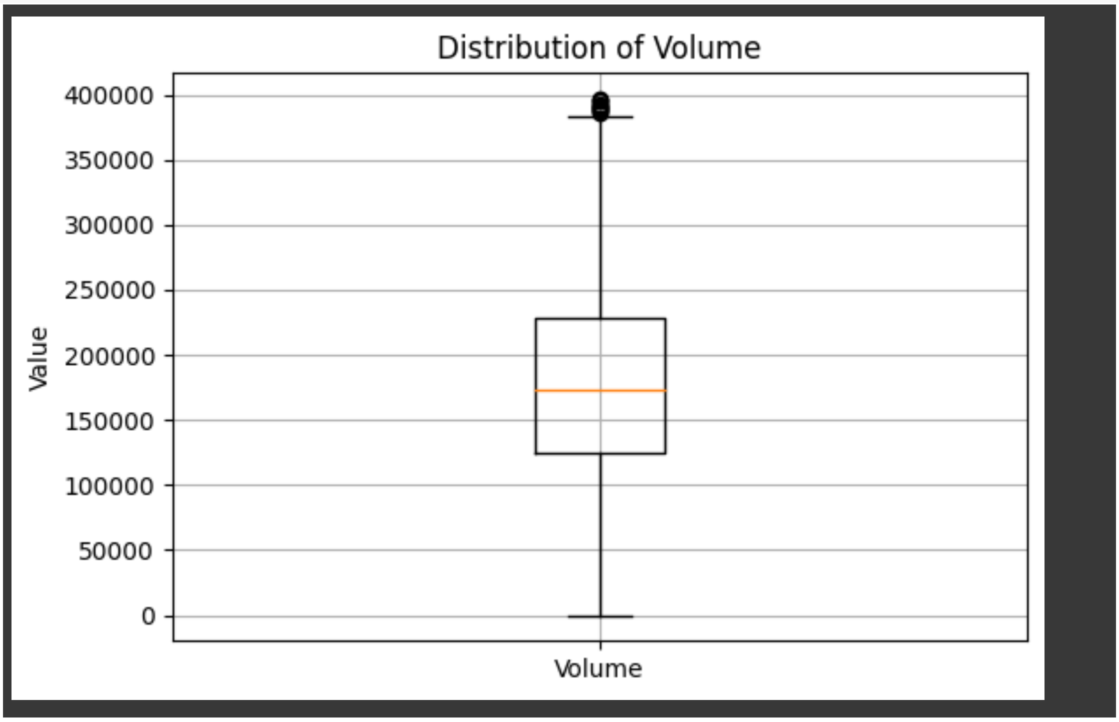
```
# Identify outliers
outliers = df[(df['Volume'] < lowerlimit) | (df['Volume'] > upperlimit)]

print("Outliers identified using IQR method:")
print('')
print(outliers)
```

```
Outliers identified using IQR method:

            Date   Close    Volume    Open    High     Low
215   2023-03-13  1916.5  426262.0  1877.1  1919.5  1875.7
466   2022-03-08  2043.3  413624.0  2001.0  2078.8  1985.8
474   2022-02-24  1926.3  409954.0  1911.9  1976.5  1878.6
758   2021-01-08  1835.4  422485.0  1915.2  1918.4  1827.8
799   2020-11-09  1854.4  475721.0  1956.0  1869.3  1861.2
...          ...     ...       ...     ...     ...     ...
1598  2017-09-05  1344.5  546280.0  1339.8  1349.7  1331.1
1602  2017-08-29  1318.9  444146.0  1320.5  1331.9  1310.6
1801  2016-11-11  1224.3  420069.0  1258.7  1265.0  1218.7
1803  2016-11-09  1273.5  783657.0  1276.8  1338.3  1268.1
1899  2016-06-24  1322.4  527205.0  1254.3  1362.6  1252.8

[74 rows x 6 columns]
```

```
df.drop(df[(df['Volume'] < lowerlimit) | (df['Volume'] > upperlimit)].index, ir

print("after removing outliers:", df.shape)
```

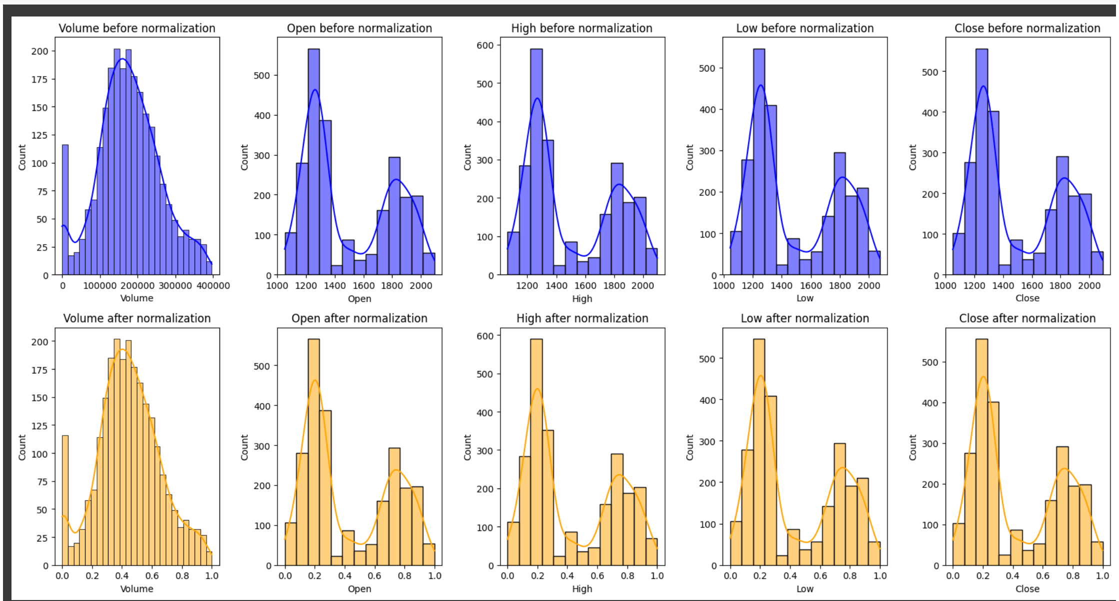
```
after removing outliers: (2437, 6)
```

```
# Plot box plot for 'Volume' feature with logarithmic scaling
plt.figure(figsize=(6, 4))
plt.boxplot(df['Volume'])
plt.title('Distribution of Volume')
plt.ylabel('Value')
plt.xticks([1], ['Volume'])
plt.grid(True)
plt.tight_layout()
plt.show()
```



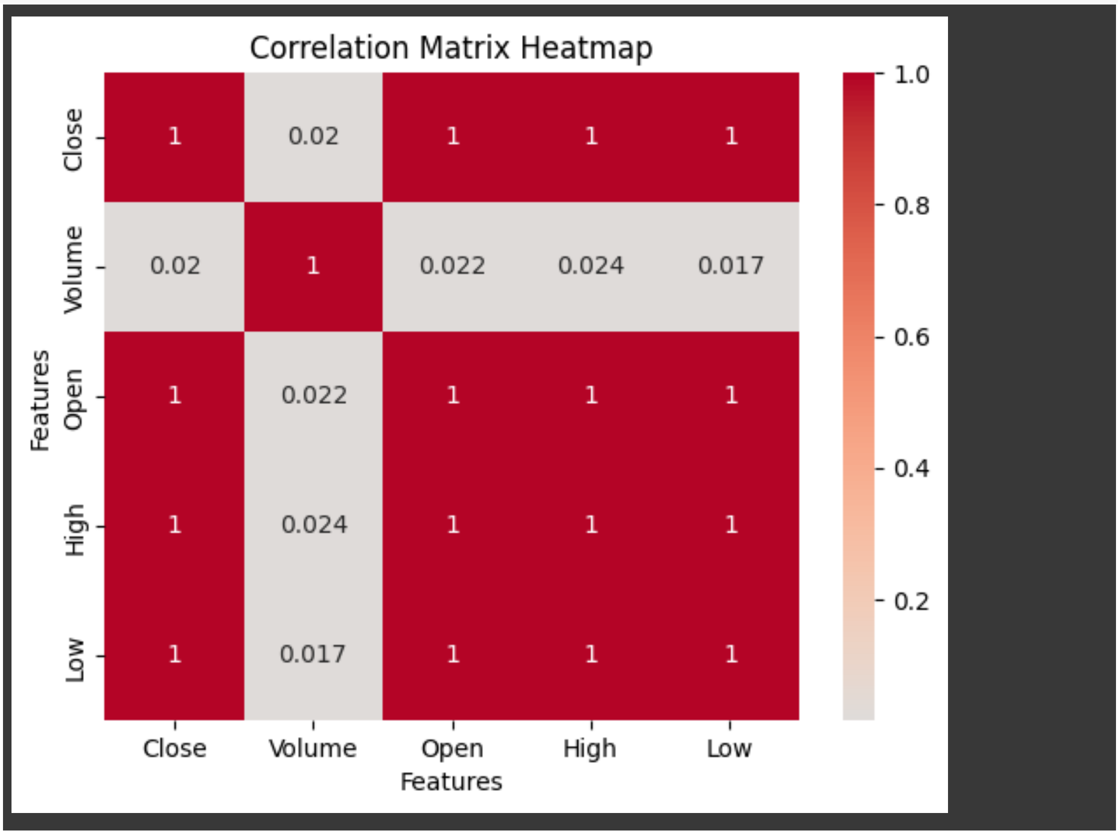

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

# Select columns to normalize
columns_to_normalize = ['Volume', 'Open', 'High', 'Low', 'Close']

# Plot distributions before normalization
plt.figure(figsize=(17, 9))
for i, col in enumerate(columns_to_normalize):
    plt.subplot(2, len(columns_to_normalize), i+1)
    sns.histplot(df[col], kde=True, color='blue')
    plt.title(f'{col} before normalization')

# Fit the scaler on the selected columns and transform the data
df[columns_to_normalize] = scaler.fit_transform(df[columns_to_normalize])
```

```
df[columns_to_normalize] = scaler.fit_transform(df[columns_to_normalize])

# Plot distributions after normalization
for i, col in enumerate(columns_to_normalize):
    plt.subplot(2, len(columns_to_normalize), len(columns_to_normalize) + i + 1
    sns.histplot(df[col], kde=True, color='orange')
    plt.title(f'{col} after normalization')

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



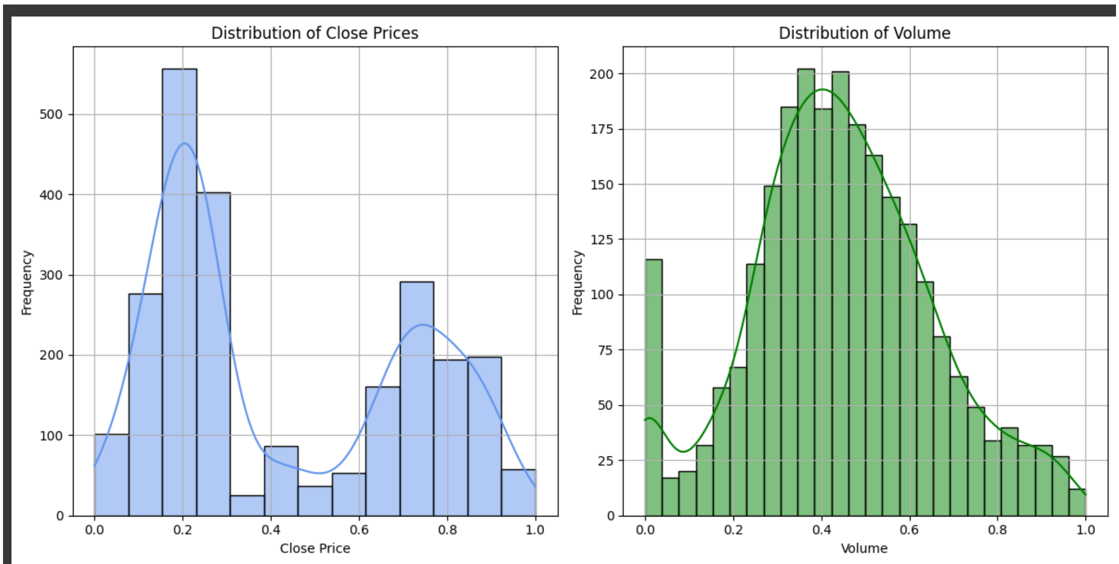

```
# Calculate correlation matrix
correlation  = df.corr()

# Create heatmap
sns.heatmap(correlation, cmap='coolwarm',
            center=0, annot=True)

# Set title and axis labels
plt.title('Correlation Matrix Heatmap')
```

```
plt.title('Correlation Matrix Heatmap')
plt.xlabel('Features')
plt.ylabel('Features')

# Show plot
plt.show()
```



Time Series Analysis: Plot distribution of Gold Price and Trading Volume

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


# Assuming df is your DataFrame containing the time series data

# Plot distribution of Close prices and Volume
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.histplot(df['Close'], kde=True, color='#6495ED')
plt.title('Distribution of Close Prices')
plt.xlabel('Close Price')
plt.ylabel('Frequency')
plt.grid(True)

plt.subplot(1, 2, 2)
sns.histplot(df['Volume'], kde=True, color='green')
plt.title('Distribution of Volume')
plt.xlabel('Volume')
plt.ylabel('Frequency')
plt.grid(True)

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

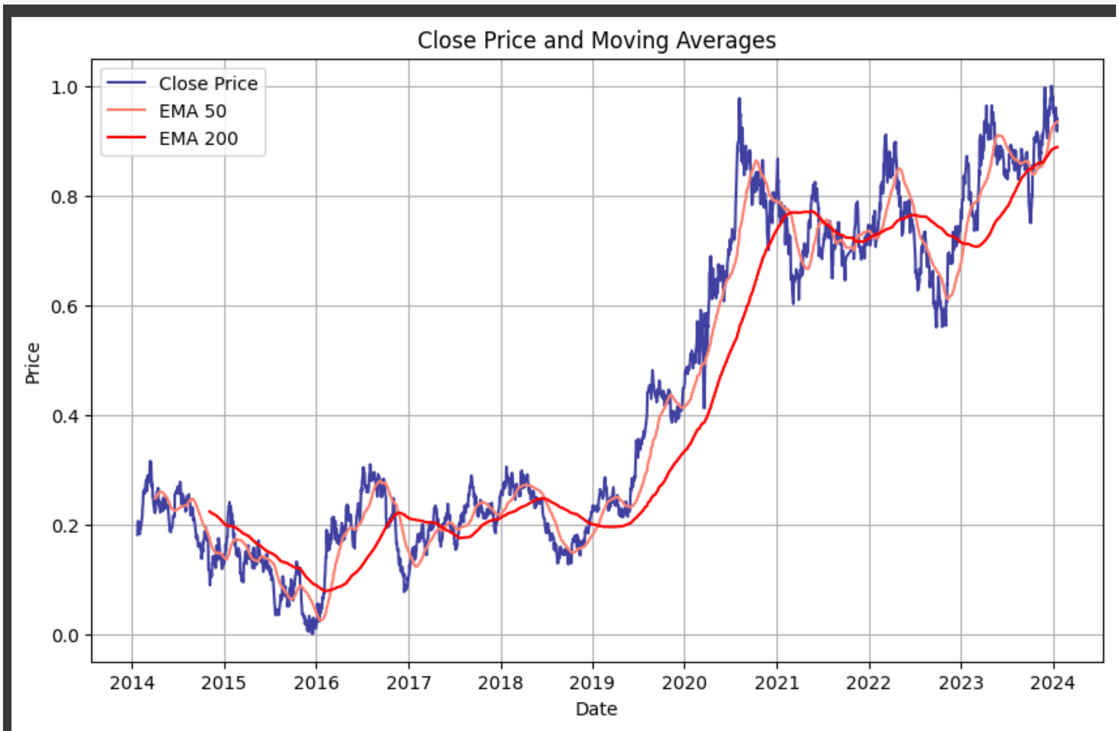

Distribution of Close Prices
Frequency
Close Price
Distribution of Volume
Frequency
Volume

```
df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True)

# Sort the DataFrame by the date index in ascending order
df = df.sort_index(ascending=True)

# Print the DataFrame to verify the changes
print(df.head())
```

```
               Close    Volume      Open      High       Low
Date
2014-01-22  0.181121  0.202344  0.181225  0.174602  0.184707
2014-01-23  0.204025  0.105119  0.176048  0.197393  0.180140
2014-01-24  0.205942  0.088230  0.204046  0.203283  0.205499
2014-01-27  0.204983  0.159882  0.209416  0.209947  0.200738
2014-01-28  0.192525  0.205279  0.195033  0.192371  0.196852
```

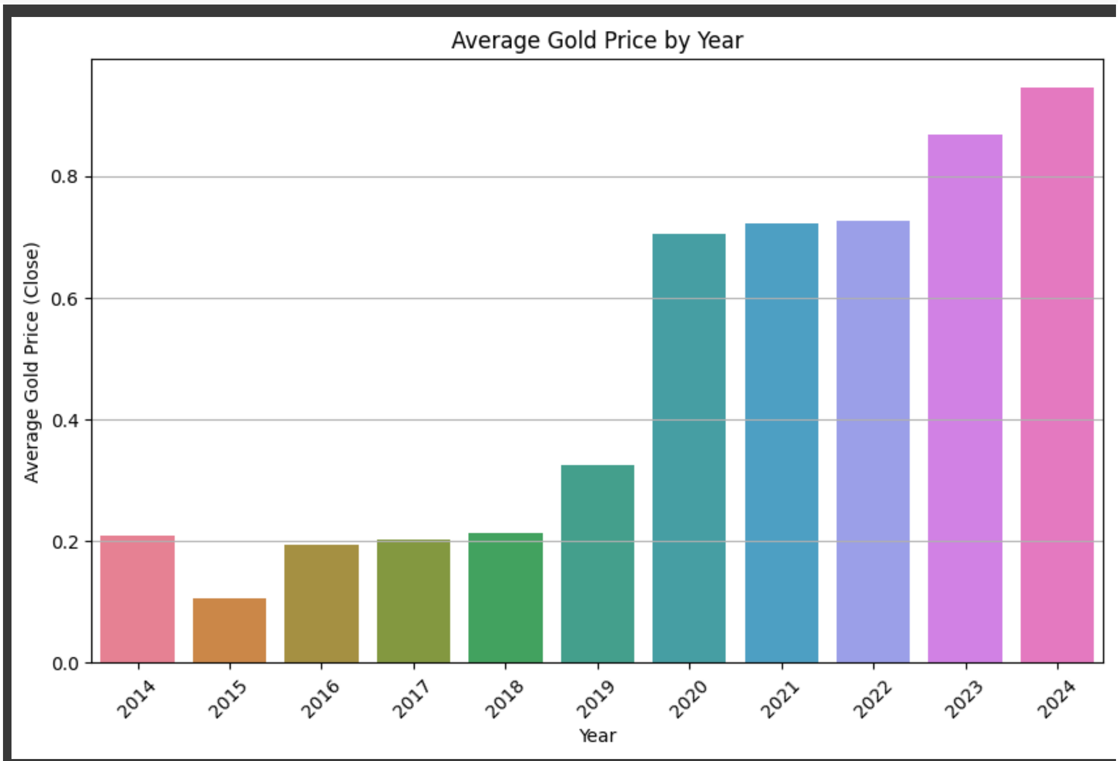
```
#Extract features from Date column
df['Month'] = df.index.month
df['Year'] = df.index.year
df['Day'] = df.index.day
#df.drop('Date')
```

```
# Moving averages
window_1 = 50
window_2 = 200
close_prices_ma_1 = df['Close'].rolling(window=window_1).mean()
close_prices_ma_2 = df['Close'].rolling(window=window_2).mean()

plt.figure(figsize=(10, 6))
plt.plot(df.index, df['Close'], label="Close Price", color='#4040a1')
plt.plot(df.index, close_prices_ma_1, label="EMA 50 ", color='Salmon')
plt.plot(df.index, close_prices_ma_2, label="EMA 200 ", color='red')
plt.title('Close Price and Moving Averages')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```

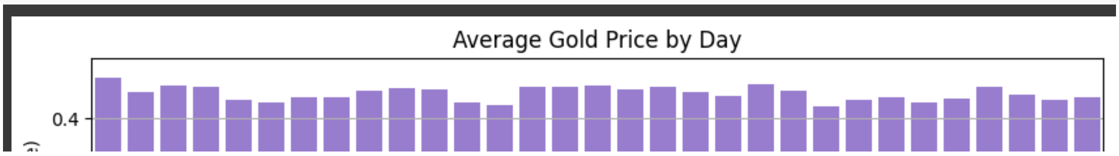


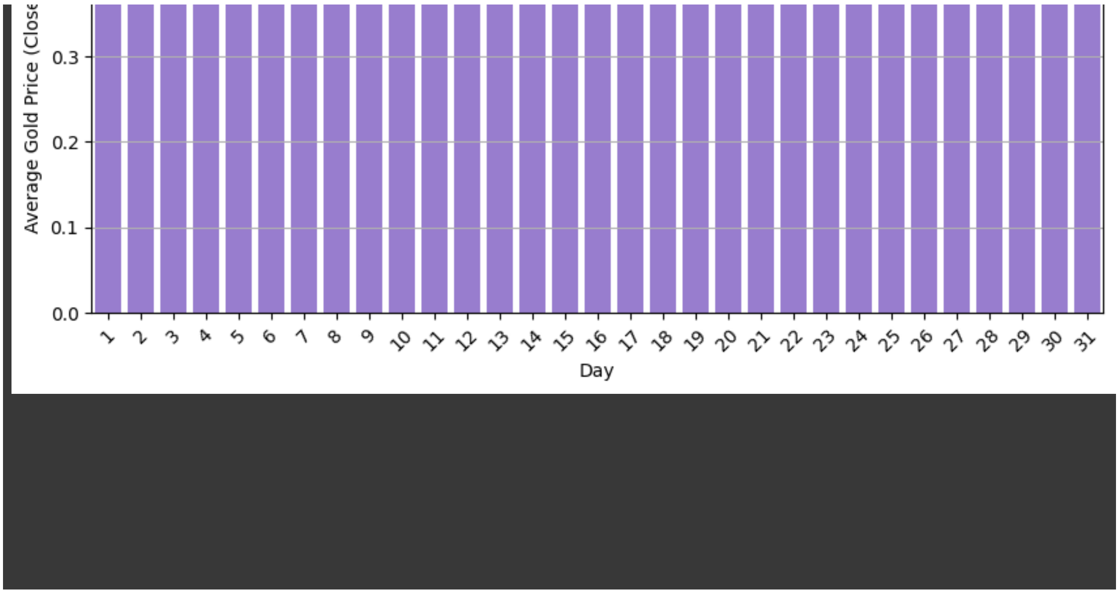

```
plt.figure(figsize=(10,6))
sns.barplot(x='Year', y='Close', data=df.groupby('Year')['Close'].mean().reset_
```

```
plt.title('Average Gold Price by Year')
plt.xlabel('Year')
plt.ylabel('Average Gold Price (Close)')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```

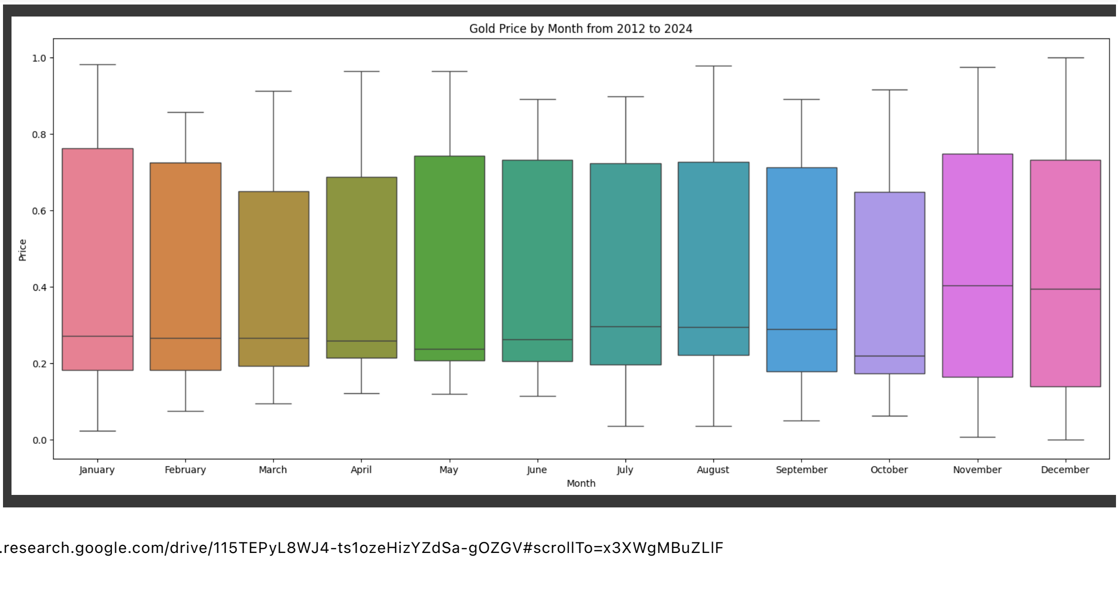



```
plt.figure(figsize=(10,4))
sns.barplot(x='Day', y='Close', data=df.groupby('Day')['Close'].mean().reset_ir
plt.title('Average Gold Price by Day')
plt.xlabel('Day')
plt.ylabel('Average Gold Price (Close)')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```

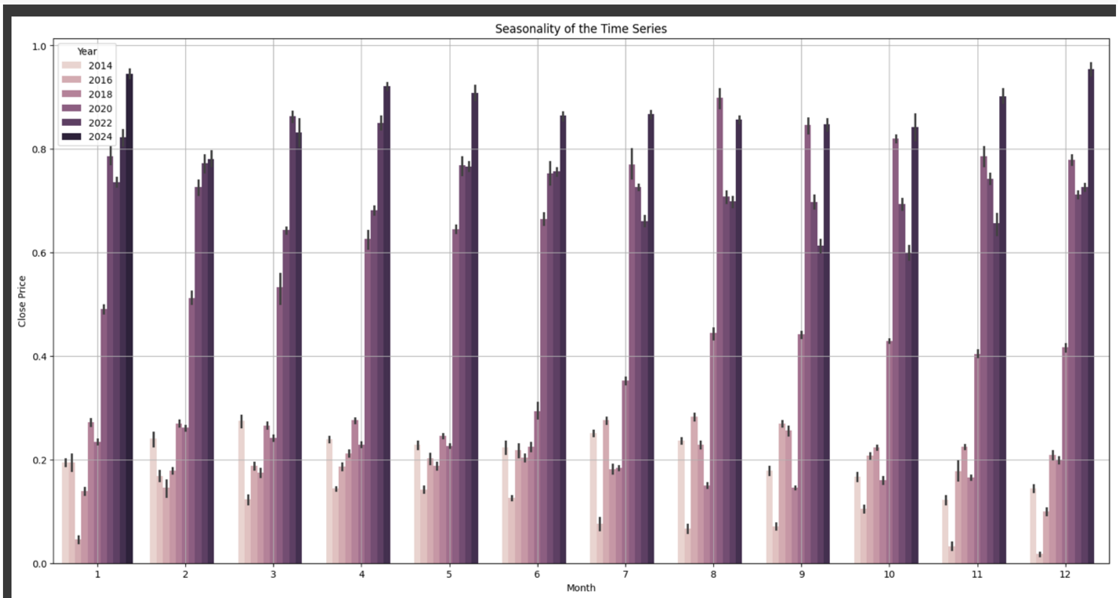




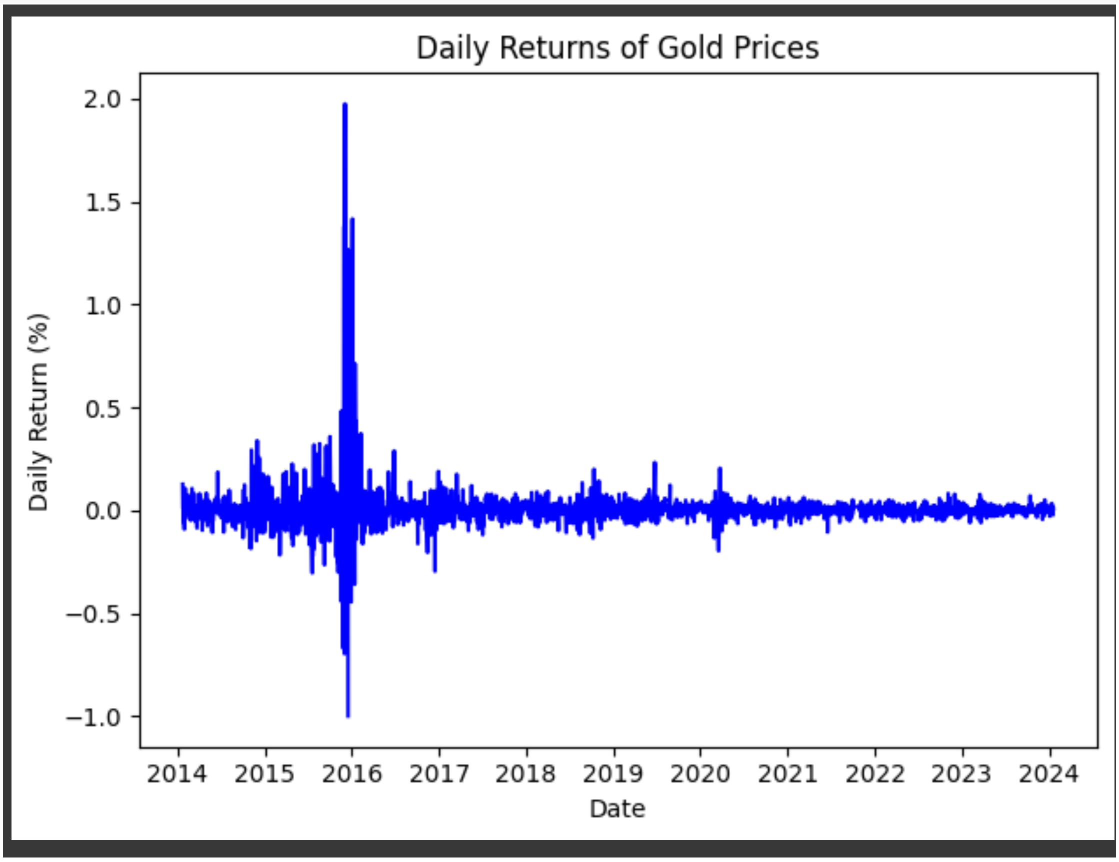

```
custom_palette = sns.color_palette("husl", 12)

fig, ax = plt.subplots(figsize=(20,8))
sns.boxplot(x=df.index.month_name(), y=df['Close'], ax=ax, palette=custom_palet
plt.title('Gold Price by Month from 2012 to 2024')
plt.xlabel('Month')
plt.ylabel('Price')
plt.show()
```



```
plt.figure(figsize=(20,10))
plt.title('Seasonality of the Time Series')

sns.barplot(x='Month', y='Close', data=df , hue='Year')

plt.xlabel('Month')
plt.ylabel('Close Price')


plt.grid(True)
plt.show()
```

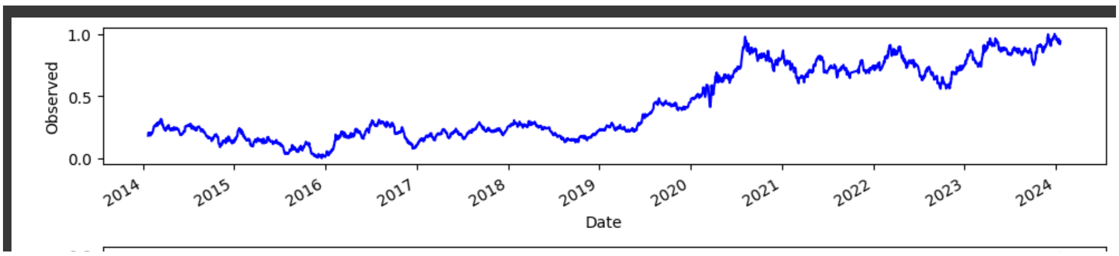


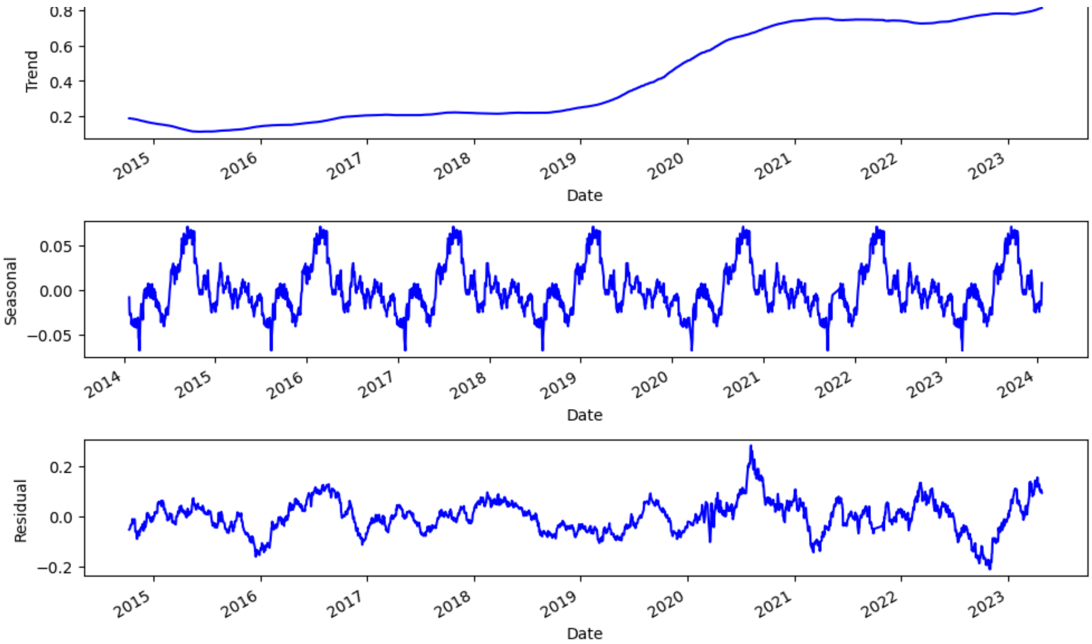
```
# Calculate daily returns
daily_returns = df['Close'].pct_change()

# Plot the daily returns
plt.plot(daily_returns.index, daily_returns,color='blue')
plt.xlabel("Date")
plt.ylabel("Daily Return (%)")
plt.title("Daily Returns of Gold Prices")
plt.tight_layout()
plt.show()
```




```
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(df['Close'], model='additive', period=365)
fig, axes = plt.subplots(4, 1, figsize=(10, 8))

# Plot each component and set the color to blue
result.observed.plot(ax=axes[0], color='blue')
axes[0].set_ylabel('Observed')
```

```
axes[0].set_ylabel('Observed')

result.trend.plot(ax=axes[1], color='blue')
axes[1].set_ylabel('Trend')

result.seasonal.plot(ax=axes[2], color='blue')
axes[2].set_ylabel('Seasonal')

result.resid.plot(ax=axes[3], color='blue')
axes[3].set_ylabel('Residual')

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






```
import xgboost as xgb
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn.linear_model import LinearRegression
from keras.models import Sequential
from keras.layers import LSTM, Dense
import tensorflow as tf
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
from math import sqrt
from sklearn.metrics import r2_score
from tensorflow.keras import regularizers
```

```
df.head(2)
```

	Close	Volume	Open	High	Low	Month	Year	Day

Date								
2014-01-22	0.181121	0.202344	0.181225	0.174602	0.184707	1	2014	22
2014-01-	0.204025	0.195119	0.176048	0.197293	0.189140	1	2014	23

Next steps: Generate code with df View recommended plots

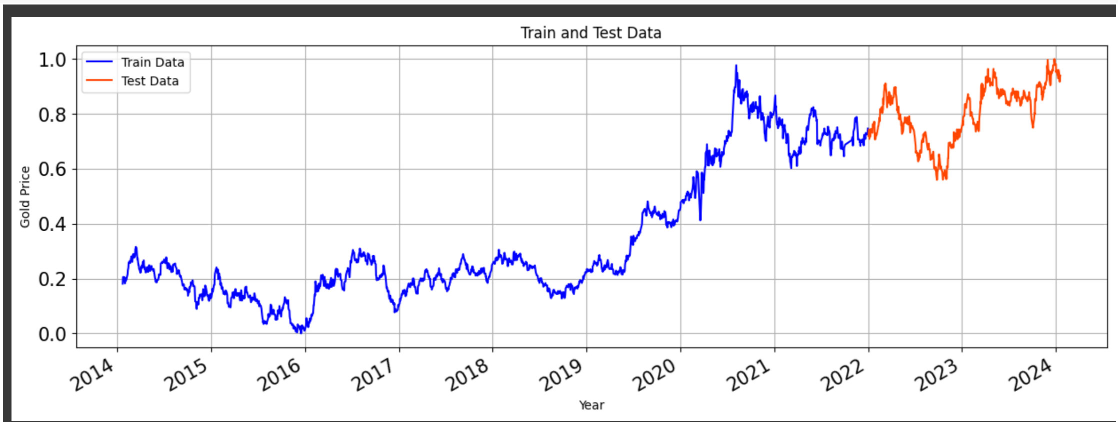
Splitting data to train and test

```
# Split the data into features (X) and target variable (y)
X = df[['Volume', 'Open', 'High', 'Low']]  # Features: Volume, Open, High, Low
y = df['Close']  # Target variable: Closing price
```

```
split_index = pd.to_datetime('2022-01-01')

train = df[df.index <= split_index]
test = df[df.index > split_index]

X_train = train.drop(columns=['Close'])
y_train = train['Close']

X_test = test.drop(columns=['Close'])
y_test = test['Close']

print(" X_train:", X_train.shape)
print(" y_train:", y_train.shape)
print(" X_test:", X_test.shape)
print(" y_test:", y_test.shape)
train_pct = len(train) / len(df) * 100
test_pct = len(test) / len(df) * 100
print()
print("Percentage of data in training set:", round(train_pct, 2), '%')
print("Percentage of data in testing set:", round(test_pct, 2), '%')
```

```
 X_train: (1929, 7)
 y_train: (1929,)
 X_test: (508, 7)
 y_test: (508,)

Percentage of data in training set: 79.15 %
Percentage of data in testing set: 20.85 %
```

```
train['Close'].plot(figsize=(15,5), color='blue')
test['Close'].plot(figsize=(15,5), fontsize=15,color='OrangeRed')
plt.grid()
plt.legend(['Train Data', 'Test Data'])
plt.title('Train and Test Data')
plt.xlabel('Year')
plt.ylabel('Gold Price')
plt.show()
```



```
param_grid = {
    'fit_intercept': [True, False],
    'positive': [True, False]
}

linear_reg = LinearRegression()
grid_search = GridSearchCV(estimator=linear_reg, param_grid=param_grid, cv=10,

grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
best_linear_reg = grid_search.best_estimator_

y_pred = best_linear_reg.predict(X_test)
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits
```

```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print evaluation metrics
print("Evaluation Metrics:")
print()
print("Best Hyperparameters:", best_params)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("Mean Absolute Error (MAE):", mae)
print("R-squared (R2):", r2)
```

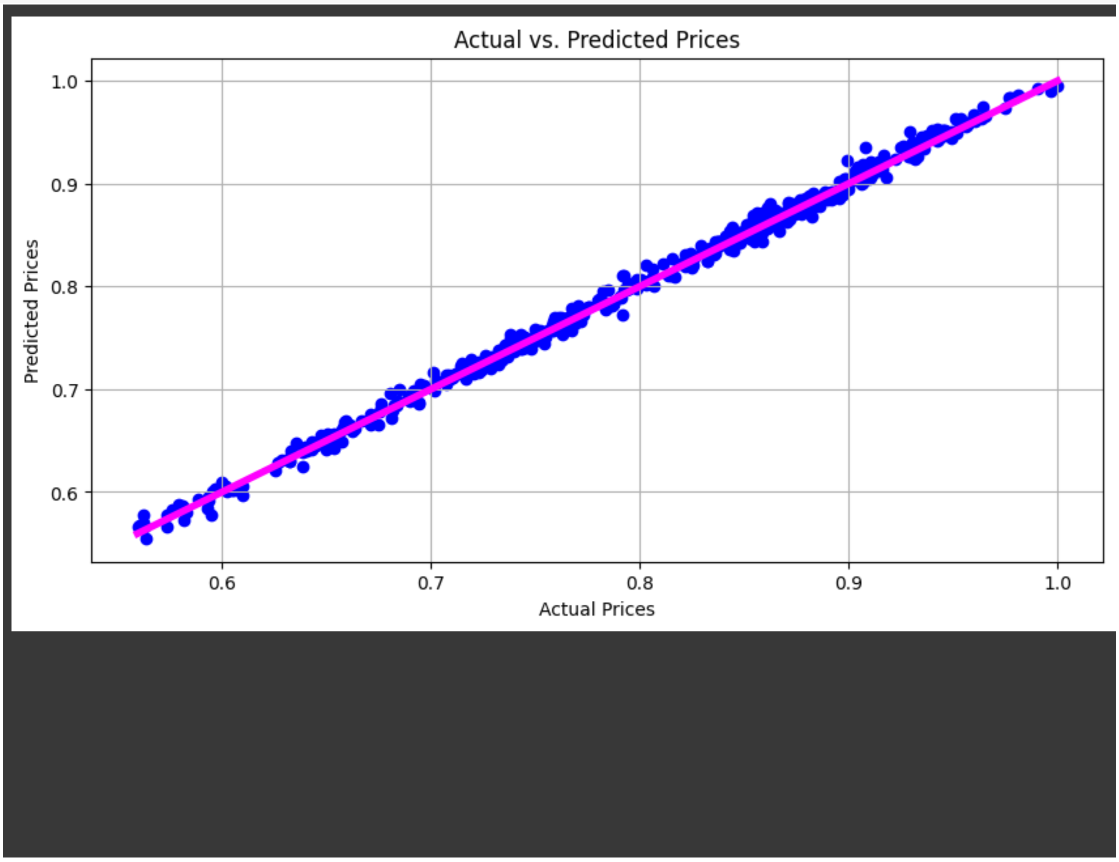
```
Evaluation Metrics:

Best Hyperparameters: {'fit_intercept': True, 'positive': False}
Mean Squared Error (MSE): 4.2639867360428126e-05
Root Mean Squared Error (RMSE): 0.00652992093064136
Mean Absolute Error (MAE): 0.005159467789286433
R-squared (R2): 0.995905881785643
```

```
test_scores = grid_search.cv_results_['split0_test_score'], grid_search.cv_resu
```

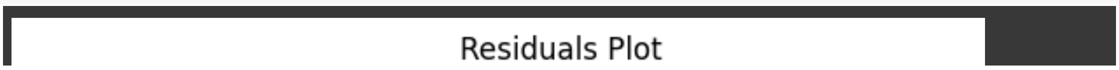
```
# Print the cross-validation scores for all folds
print("Cross-validation scores for the Last Model:")
for i, scores in enumerate(zip(*test_scores)):
    print(f"CV {i + 1}: {scores}")
```

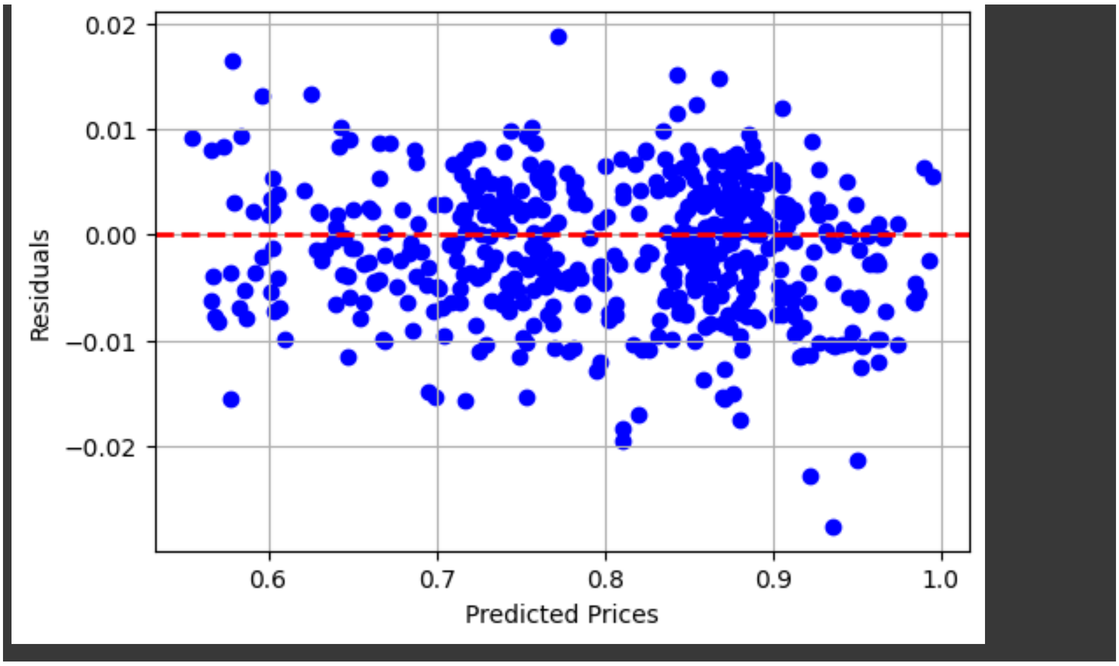
```
Cross-validation scores for the Last Model:
CV 1: (0.9838340741883447, 0.9765694511378007, 0.9934748068949113, 0.993460
CV 2: (0.9876286389829033, 0.9846166900330708, 0.9953104533476099, 0.994528
CV 3: (0.9838291574360771, 0.9764923880556023, 0.9934639195163804, 0.993436
CV 4: (0.9875575533611534, 0.984542289102779, 0.9953070039344546, 0.9944946
```

```
plt.figure(figsize=(10, 5))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], lw=4, colc
plt.title('Actual vs. Predicted Prices')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.grid(True)
plt.show()
```




```
residuals = y_test - y_pred
plt.figure(figsize=(6, 4))
plt.scatter(y_pred, residuals, color='blue')
plt.axhline(y=0, color='r', linestyle='--', lw=2)
plt.title('Residuals Plot')
plt.xlabel('Predicted Prices')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()
```





LSTM model for predictive analytics

```
def create_sequences(df, column_name, sequence_length):
    sequence_as_np = df[column_name].to_numpy()
    X = []
    y = []

    for i in range(len(sequence_as_np) - sequence_length):
        row = [[a] for a in sequence_as_np[i:i + sequence_length]]
        X.append(row)
        label = sequence_as_np[i + sequence_length]
        y.append(label)

    return np.array(X), np.array(y)
```

```
SEQUENCE_LENGTH = 30
X, y = create_sequences(df, 'Close', SEQUENCE_LENGTH)
X = X.reshape(X.shape[0], -1)

# Normalize data
scaler = MinMaxScaler(feature_range=(0, 1))
X = scaler.fit_transform(X)
y = scaler.fit_transform(y.reshape(-1, 1))
```

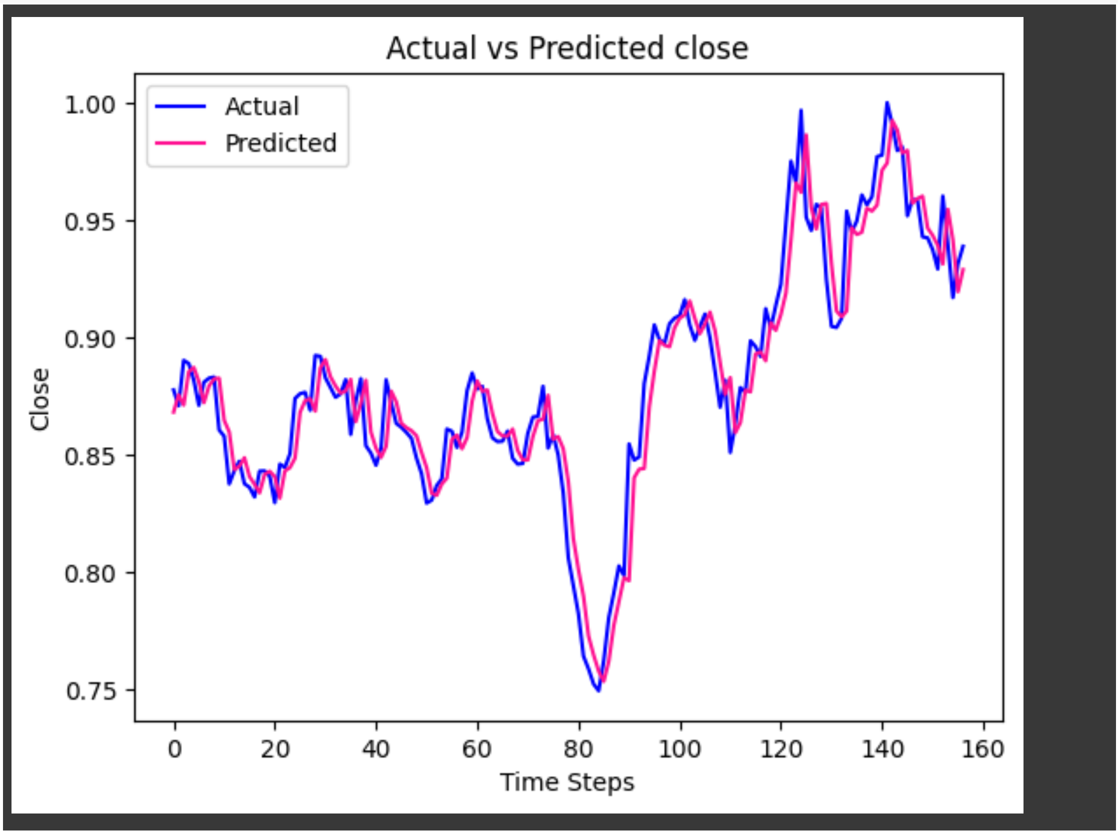
```
input = 2250
X_train, y_train = X[:input], y[:input]
X_test, y_test = X[input:], y[input:]
X_train.shape, y_train.shape , X_test.shape, y_test.shape
X_train = X_train.reshape(X_train.shape[0], SEQUENCE_LENGTH, 1)
X_test = X_test.reshape(X_test.shape[0], SEQUENCE_LENGTH, 1)
model = Sequential()
model.add(LSTM(units=100, activation='relu', return_sequences=False, input_shap
model.add(Dense(units=1))

optimizer = Adam(learning_rate=0.001)
model.compile(optimizer=optimizer, loss='mean_squared_error')

early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_wei
```

```
history = model.fit(X_train, y_train, epochs=50, batch_size=16, validation_spli
y_predlstm = model.predict(X_test)

y_predlstm = y_predlstm.reshape(-1, 1)

y_predlstm  = scaler.inverse_transform(y_predlstm )
y_test = scaler.inverse_transform(y_test)

mse = mean_squared_error(y_test, y_predlstm)
rmse = sqrt(mse)
r_squared = r2_score(y_test, y_predlstm)

print(f'Mean Squared Error on Test Set: {mse}')
print(f'Root Mean Squared Error on Test Set: {rmse}')
print(f'R-squared on Test Set: {r_squared}')
```

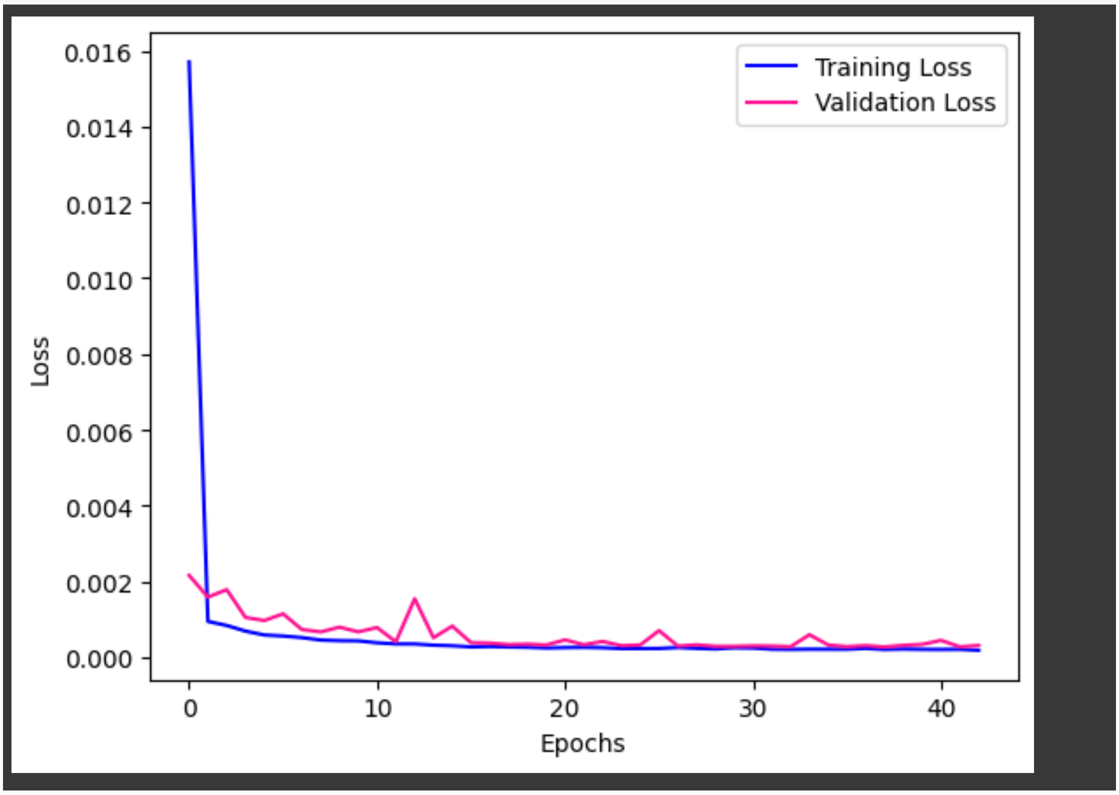
```
Epoch 1/50
113/113 [==============================] - 9s 54ms/step - loss: 0.0157 - va
Epoch 2/50
113/113 [==============================] - 6s 57ms/step - loss: 9.5287e-04
Epoch 3/50
113/113 [==============================] - 5s 44ms/step - loss: 8.4572e-04
Epoch 4/50
113/113 [==============================] - 3s 29ms/step - loss: 6.9687e-04
Epoch 5/50
113/113 [==============================] - 3s 26ms/step - loss: 5.9504e-04
Epoch 6/50
113/113 [==============================] - 4s 33ms/step - loss: 5.6822e-04
Epoch 7/50
113/113 [==============================] - 3s 23ms/step - loss: 5.2573e-04
Epoch 8/50
113/113 [==============================] - 3s 23ms/step - loss: 4.6149e-04
Epoch 9/50
113/113 [==============================] - 3s 23ms/step - loss: 4.4486e-04
Epoch 10/50
113/113 [==============================] - 3s 26ms/step - loss: 4.3950e-04
Epoch 11/50
113/113 [==============================] - 4s 31ms/step - loss: 3.8886e-04
Epoch 12/50
113/113 [==============================] - 3s 23ms/step - loss: 3.6027e-04
Epoch 13/50
113/113 [==============================] - 3s 23ms/step - loss: 3.5866e-04
Epoch 14/50
113/113 [==============================] - 3s 22ms/step - loss: 3.2605e-04
Epoch 15/50
113/113 [==============================] - 3s 28ms/step - loss: 3.1124e-04
Epoch 16/50
113/113 [==============================] - 3s 30ms/step - loss: 2.8032e-04
```

```
Epoch 17/50
113/113 [==============================] - 4s 38ms/step - loss: 2.9084e-04
Epoch 18/50
113/113 [==============================] - 4s 33ms/step - loss: 2.7986e-04
Epoch 19/50
113/113 [==============================] - 5s 42ms/step - loss: 2.7261e-04
Epoch 20/50
113/113 [==============================] - 3s 24ms/step - loss: 2.5233e-04
Epoch 21/50
113/113 [==============================] - 3s 23ms/step - loss: 2.6333e-04
Epoch 22/50
113/113 [==============================] - 3s 23ms/step - loss: 2.6990e-04
Epoch 23/50
113/113 [==============================] - 3s 23ms/step - loss: 2.5900e-04
Epoch 24/50
113/113 [==============================] - 4s 34ms/step - loss: 2.3646e-04
Epoch 25/50
113/113 [==============================] - 4s 38ms/step - loss: 2.3808e-04
Epoch 26/50
113/113 [==============================] - 5s 48ms/step - loss: 2.3935e-04
Epoch 27/50
113/113 [==============================] - 4s 31ms/step - loss: 2.6468e-04
Epoch 28/50
113/113 [==============================] - 3s 25ms/step - loss: 2.4216e-04
Epoch 29/50
113/113 [==============================] - 3s 22ms/step - loss: 2.2666e-04
Epoch 30/50
```

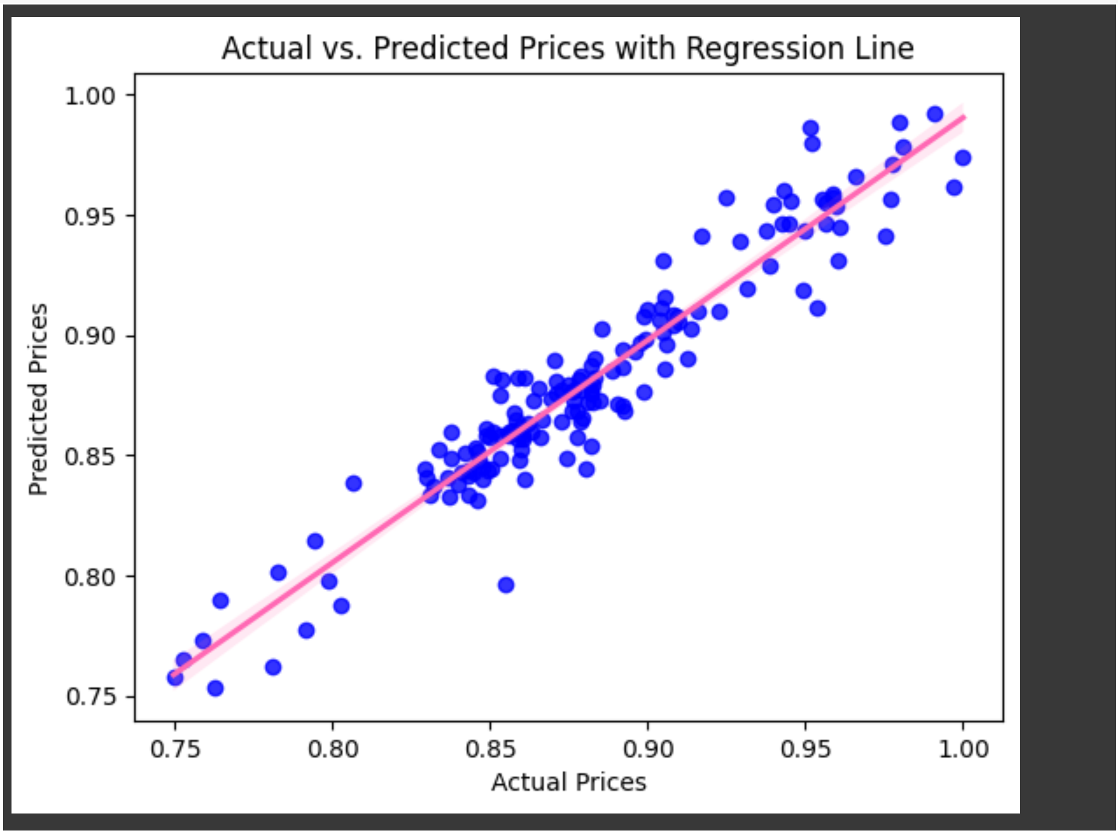
```
plt.plot(y_test, label='Actual',color='blue')
plt.plot(y_predlstm, label='Predicted',color='DeepPink')
plt.title('Actual vs Predicted close')
plt.xlabel('Time Steps')
plt.ylabel('Close')
plt.legend()
plt.show()
```



```
plt.plot(history.history['loss'], label='Training Loss',color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss',color='DeepPink')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

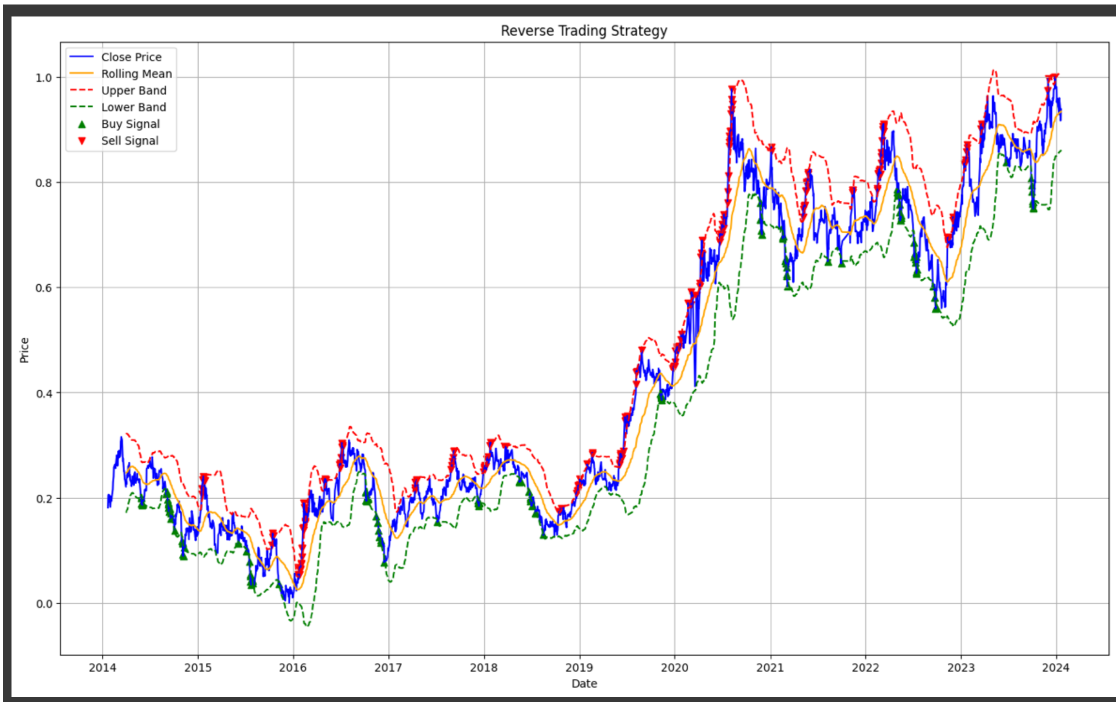



```
sns.regplot(x=y_test.flatten(), y=y_predlstm.flatten(), scatter_kws={'color': '
plt.title('Actual vs. Predicted Prices with Regression Line')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.show()
```




```
lookback_period = 50
entry_threshold = 2.0
exit_threshold = 0.0

df['RollingMean'] = df['Close'].rolling(window=lookback_period).mean()
df['RollingStd'] = df['Close'].rolling(window=lookback_period).std()

# Calculate upper and lower bands for entry and exit
df['UpperBand'] = df['RollingMean'] + entry_threshold * df['RollingStd']
df['LowerBand'] = df['RollingMean'] - entry_threshold * df['RollingStd']
exit_band = df['RollingMean'] + exit_threshold * df['RollingStd']

# Initialize trading signals
df['Signal'] = 0

# Generate trading signals

for i in range(lookback_period, len(df)):
    if df['Close'].iloc[i] > df['UpperBand'].iloc[i]:
        df.at[df.index[i], 'Signal'] = -1  # Sell signal (price above upper bar
    elif df['Close'].iloc[i] < df['LowerBand'].iloc[i]:
        df.at[df.index[i], 'Signal'] = 1  # Buy signal (price below lower band)
    elif df['Close'].iloc[i] > exit_band.iloc[i]:
        df.at[df.index[i], 'Signal'] = 0  # Exit signal (price above exit band)
    elif df['Close'].iloc[i] < exit_band.iloc[i]:
        df.at[df.index[i], 'Signal'] = 0  # Exit signal (price below exit band)

# Backtesting
initial_capital = 100000  # Initial capital in dollars
position = 0  # Initial position
cash = initial_capital  # Initial cash
portfolio_value = []  # Portfolio value over time

for i in range(lookback_period, len(df)):
```

```
for i in range(lookback_period, len(df)):
    if df['Signal'].iloc[i] == 1:
        # Enter long position
        position = cash / df['Close'].iloc[i]  # Invest all available cash
        cash = 0  # No remaining cash after buying
    elif df['Signal'].iloc[i] == -1:
        # Enter short position
        cash += position * df['Close'].iloc[i]  # Sell all owned assets
        position = 0  # No remaining position after selling
    elif df['Signal'].iloc[i] == 0:
        # Exit position
        cash += position * df['Close'].iloc[i]  # Sell all owned assets
        position = 0  # No remaining position after selling

    # Calculate portfolio value
    portfolio_value.append(cash + position * df['Close'].iloc[i])

# Calculate performance metrics
total_return = (portfolio_value[-1] - initial_capital) / initial_capital
daily_returns = np.diff(portfolio_value) / portfolio_value[:-1]
sharpe_ratio = np.mean(daily_returns) / np.std(daily_returns) * np.sqrt(252)  #
max_drawdown = np.max(np.maximum.accumulate(portfolio_value) - portfolio_value)

# Plotting
# Plotting
plt.figure(figsize=(17, 10))
plt.plot(df.index, df['Close'], label='Close Price', color='blue')
plt.plot(df.index, df['RollingMean'], label='Rolling Mean', color='orange')
plt.plot(df.index, df['UpperBand'], label='Upper Band', color='red', linestyle=
plt.plot(df.index, df['LowerBand'], label='Lower Band', color='green', linestyl

# Filter 'Close' prices for buy and sell signals

buy_indices = df[df['Signal'] == 1].index
sell_indices = df[df['Signal'] == -1].index
buy_prices = df.loc[df['Signal'] == 1, 'Close']
sell_prices = df.loc[df['Signal'] == -1, 'Close']

# Plot buy and sell signals
plt.scatter(buy_indices, buy_prices, label='Buy Signal', marker='^', color='gre
plt.scatter(sell_indices, sell_prices, label='Sell Signal', marker='v', color='

plt.xlabel('Date')
plt.ylabel('Price')
plt.title('Reverse Trading Strategy')
plt.legend()
plt.grid(True)
plt.show()
```


Reverse Trading Strategy
Close Price
Rolling Mean
Upper Band
Lower Band
Buy Signal
Sell Signal
Price
1.0
0.8
0.6
0.4
0.2
0.0
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Date

```
# Count the number of buy and sell signals
total_trades = len(df[df['Signal'] != 0])

# Count the number of successful buy and sell signals
successful_buy_trades = len(df[(df['Signal'] == 1) & (df['Close'] < df['UpperBa
successful_sell_trades = len(df[(df['Signal'] == -1) & (df['Close'] > df['Lower

# Calculate win rates
buy_win_rate = successful_buy_trades / total_trades
sell_win_rate = successful_sell_trades / total_trades

# Print win rates
print("Buy Win Rate:", buy_win_rate)
print("Sell Win Rate:", sell_win_rate)
```

```
Buy Win Rate: 0.3888888888888889
Sell Win Rate: 0.6111111111111112
```