Predicting Disney Stock Price Using Time Series Data Code Document

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Library and Dataset Importation

```
# I will import the necessary libraries needed for data mining,
exploratory data analysis, and data preparation here.

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.stattools import adfuller
import pmdarima as pm
from pmdarima import auto_arima
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
import warnings

warnings.filterwarnings('ignore')

# I will read in the dataset and display it using the head() function.

disney_stock_data =
'https://raw.githubusercontent.com/SosukeAizen5/Portfolio/refs/heads/
main/DSC%20680%20Applied%20Data%20Science/DIS.csv'

disney = pd.read_csv(disney_stock_data)

disney.head()
```

	Date	Open	High	Low	Close	Volume
0	1962-01-02	0.057941	0.059886	0.057941	0.057941	841958
1	1962-01-03	0.057941	0.058914	0.057941	0.058719	801865
2	1962-01-04	0.058719	0.058914	0.058331	0.058719	962238
3	1962-01-05	0.058719	0.059108	0.058525	0.058914	962238
4	1962-01-08	0.058914	0.059691	0.057553	0.058719	1282984

Data Preparation

```
# I will now check the data types of each column's observations within the dataset. I can do this using .dtypes.

disney.dtypes
```

```
Date       object
Open      float64
High      float64
Low       float64
Close     float64
Volume      int64
dtype: object
```

```
# Since we are dealing with time series data, I must convert the Date column into a format recognized by Python as time
# series data, which is why I will use pd.to_datetime(). I also am choosing to convert the Volume column to the float type
# to keep the data types the same (it is not necessary yet it is my preference to do so) using .astype().

disney['Date'] = pd.to_datetime(disney['Date'])
disney['Volume'] = disney['Volume'].astype(float)

disney.dtypes
```

```
Date      datetime64[ns]
Open             float64
High             float64
Low              float64
Close            float64
Volume           float64
dtype: object
```

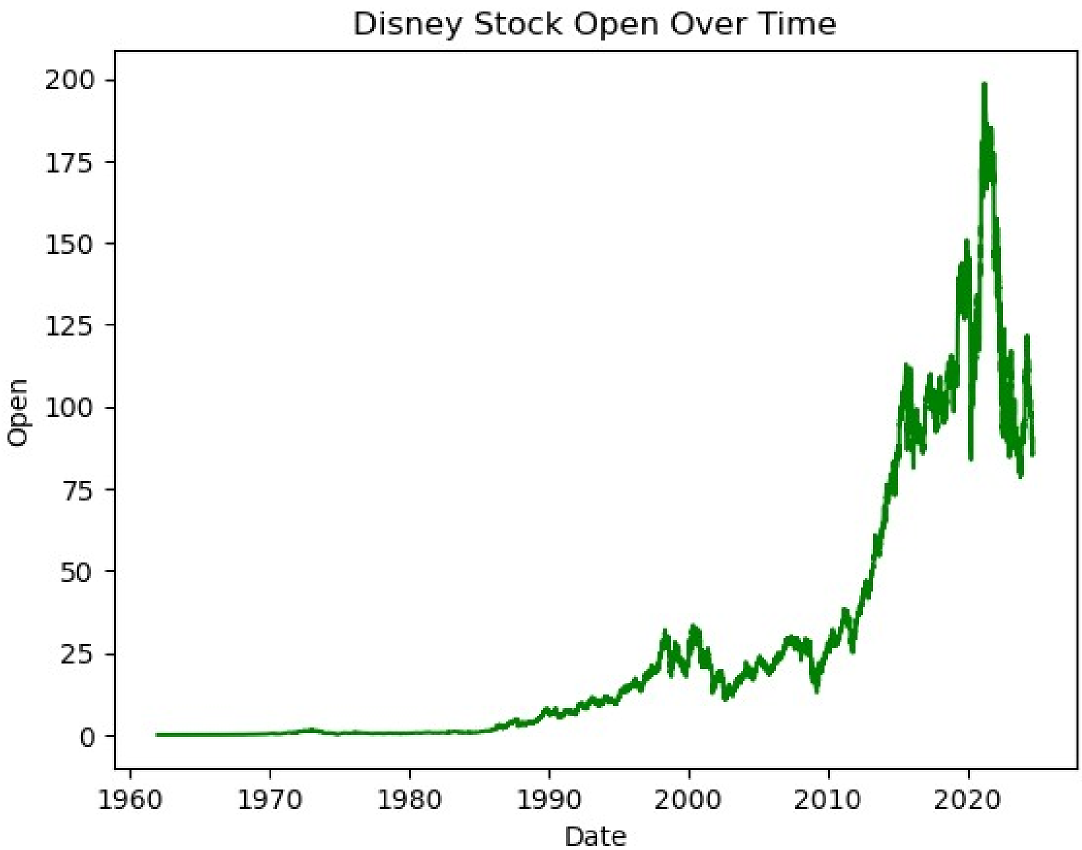
```
# The dataset is now ready for the exploratory data analysis stage. I will print the dataset to show the current changes.

disney.head()
```

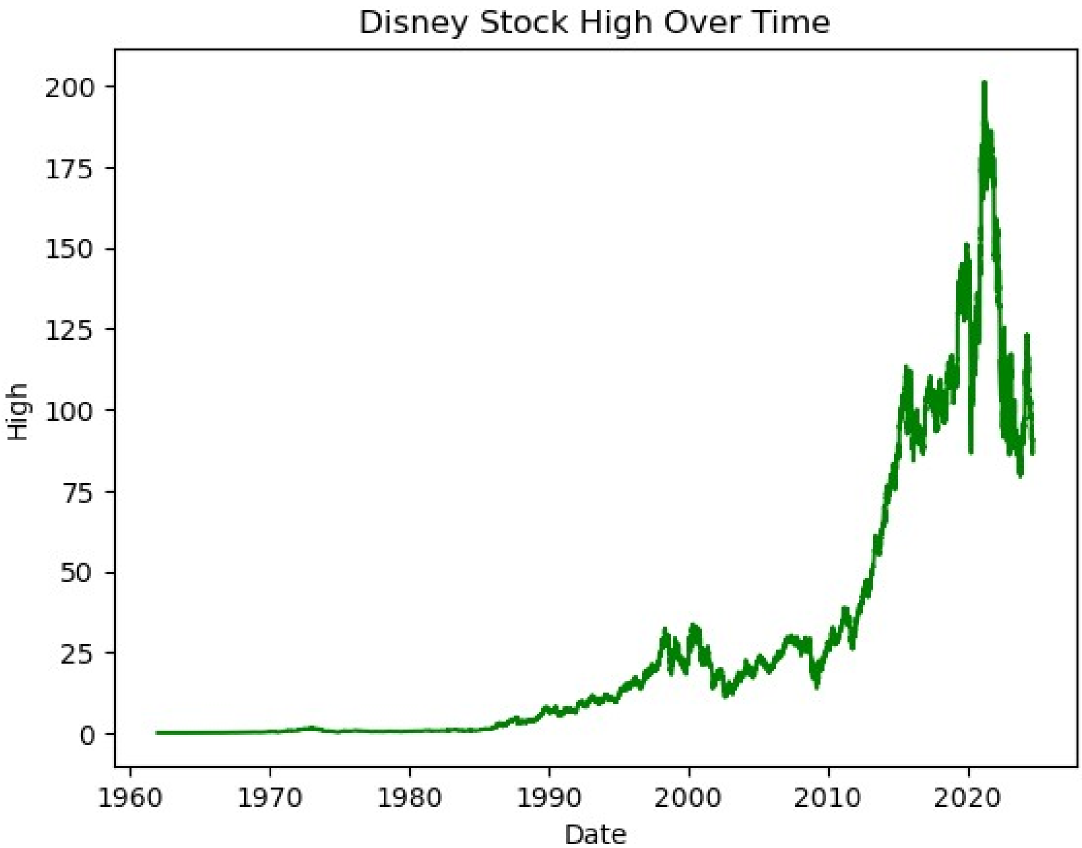
	Date	Open	High	Low	Close	Volume
0	1962-01-02	0.057941	0.059886	0.057941	0.057941	841958.0
1	1962-01-03	0.057941	0.058914	0.057941	0.058719	801865.0
2	1962-01-04	0.058719	0.058914	0.058331	0.058719	962238.0
3	1962-01-05	0.058719	0.059108	0.058525	0.058914	962238.0
4	1962-01-08	0.058914	0.059691	0.057553	0.058719	1282984.0

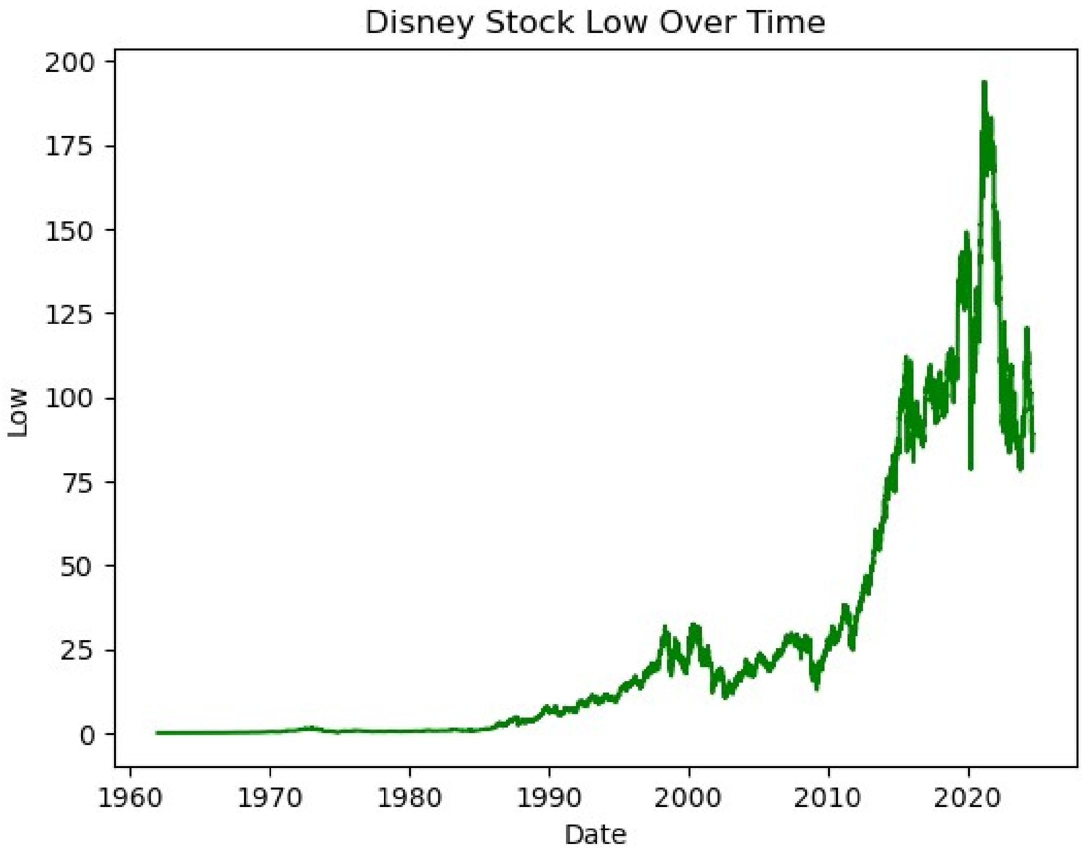
Initial Exploratory Data Analysis

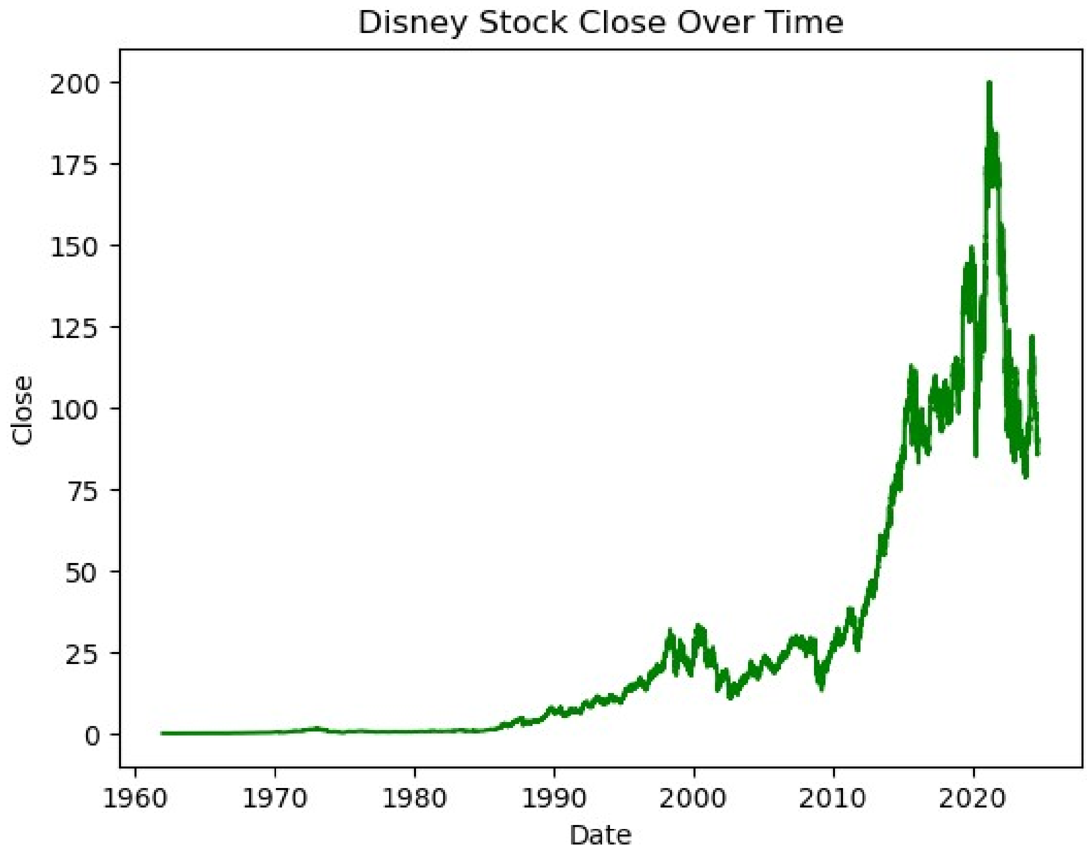
```
# I'd like to visualize multiple line charts highlighting the stock price trends over time for each variable. I will craft a
```

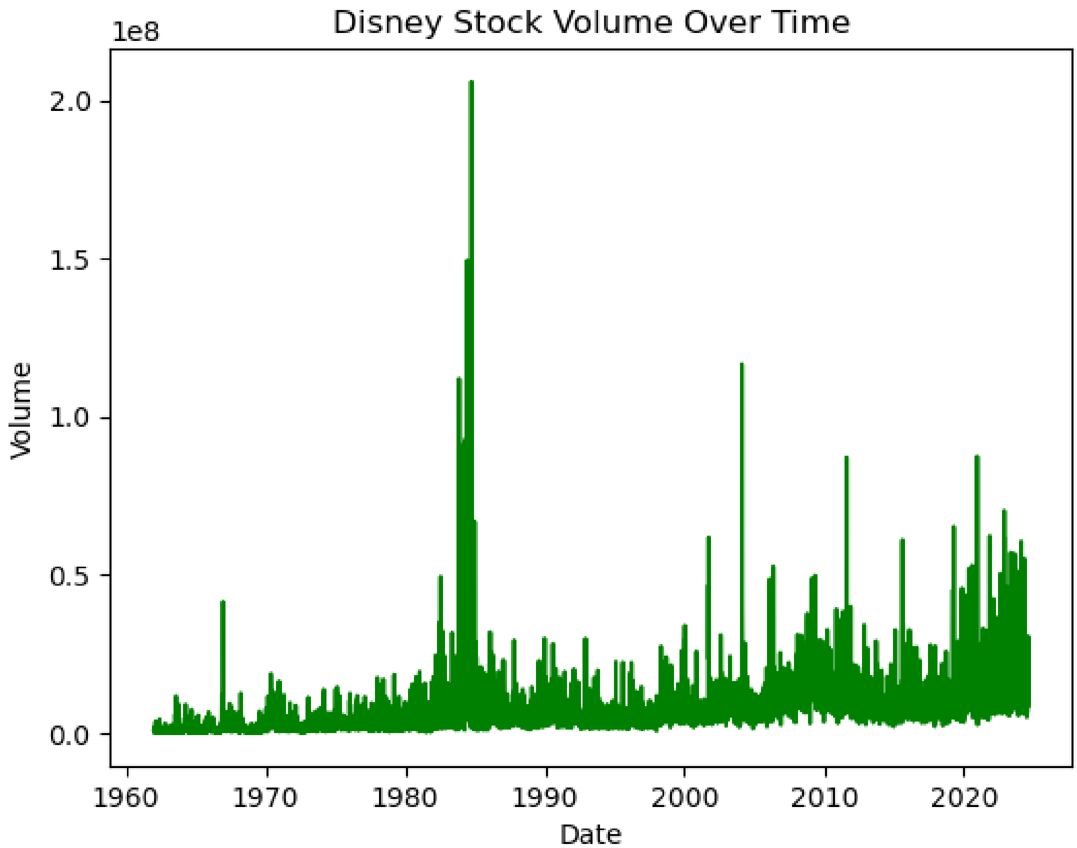
```python
# for loop that will access a function created to output a line chart for each variable in the dataset. The function will
# take a DataFrame and a column as arguments.

def make_line_charts(data, col):
    plt.plot(data['Date'], data[col], color = 'green')
    plt.title(f'Disney Stock {col} Over Time')
    plt.xlabel('Date')
    plt.ylabel(f'{col}')
    plt.show()

for col in disney.drop(['Date'], axis = 1).columns:
    make_line_charts(disney, col)
```



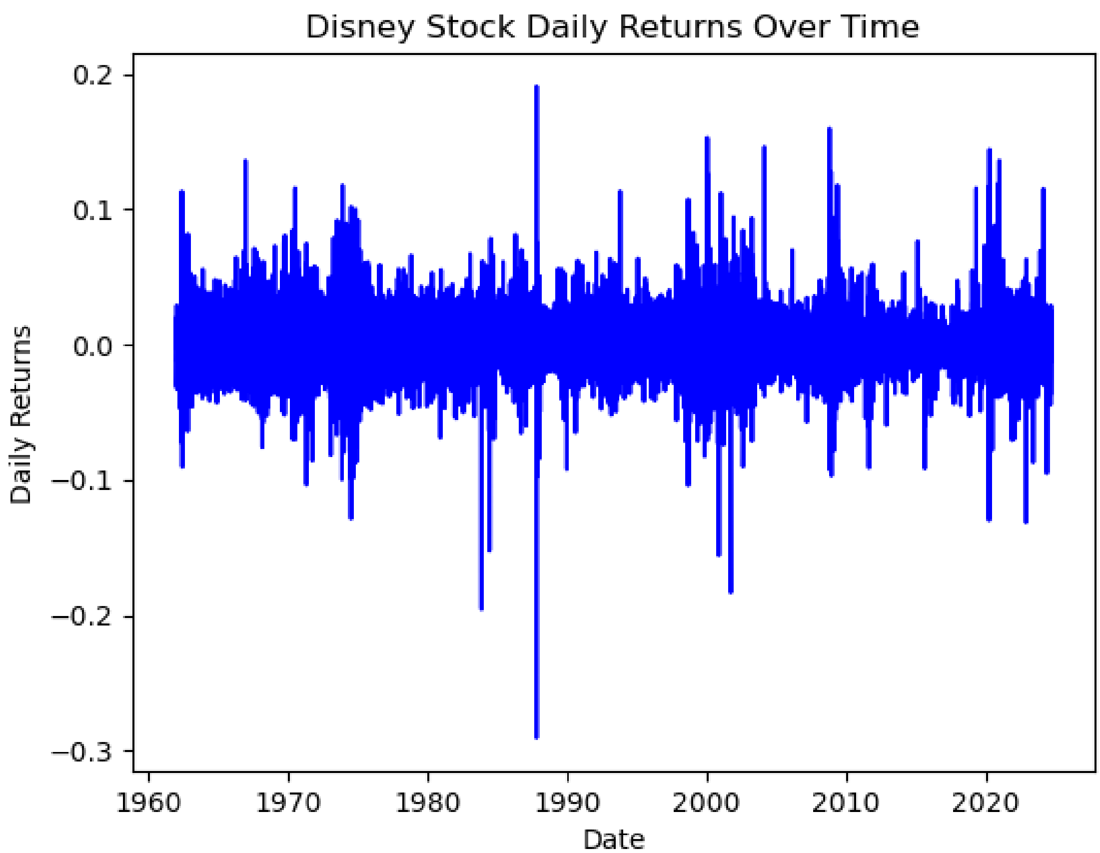

Disney Stock High Over Time
High
Date
0
25
50
75
100
125
150
175
200
1960
1970
1980
1990
2000
2010
2020


Disney Stock Low Over Time
Low
Date
0
25
50
75
100
125
150
175
200
1960
1970
1980
1990
2000
2010
2020


Disney Stock Close Over Time
200
175
150
125
100
75
50
25
0
Close
1960
1970
1980
1990
2000
2010
2020
Date




```
# Next, I wish to visualize the daily stock price returns, which can
be calculated by taking the percent change of the
# closing stock price from the previous trading day. Laying these
daily returns out over time can shed light on how volatile
# Disney stock has been throughout the years.

disney['Daily Return'] = disney['Close'].pct_change()

plt.plot(disney['Date'], disney['Daily Return'], color = 'blue')
plt.title('Disney Stock Daily Returns Over Time')
plt.xlabel('Date')
plt.ylabel('Daily Returns')

plt.show()
```

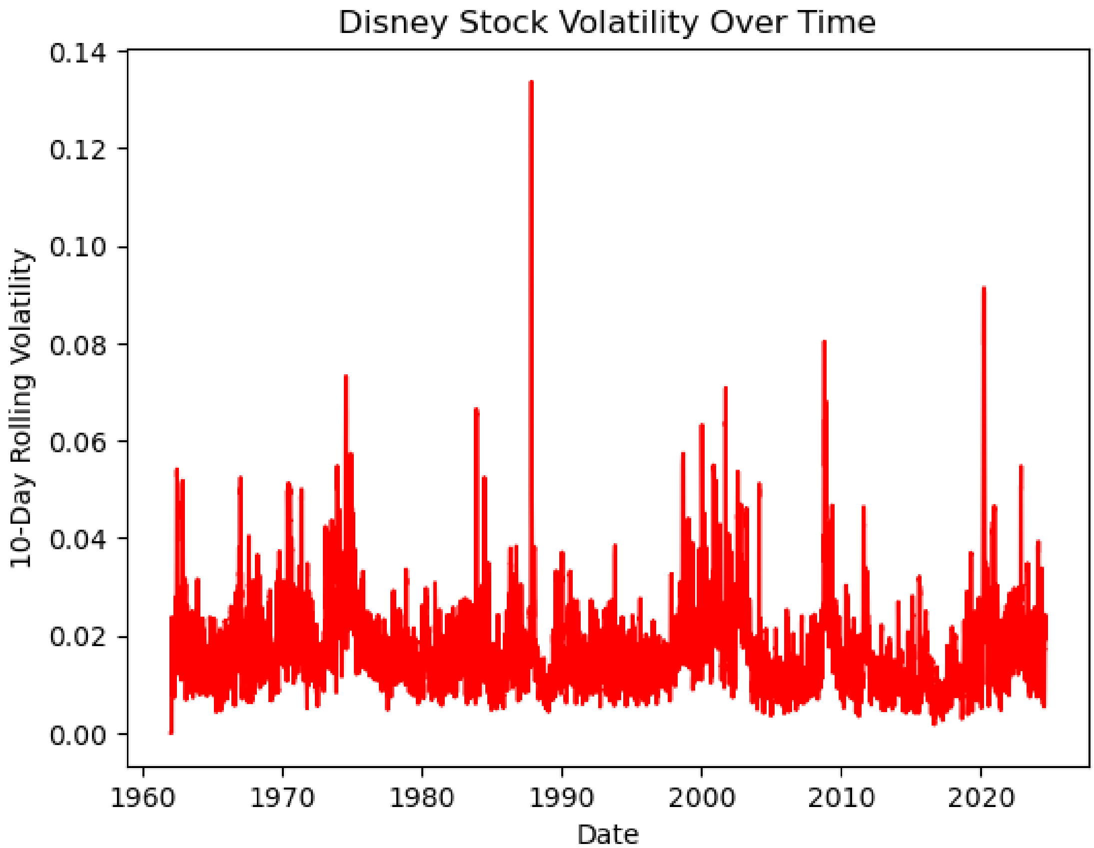



```
# Now that the daily returns chart shows an image of how volatile Disney stock has been over time, I'd like to quantify this
# volatility even further by setting volatility equal to the 10-day (two-week trading period) rolling standard deviation of
# daily returns. By adding this feature into the dataset, we can see the level of volatility over a 10-day period as a
# number rather than an image left for interpretation.

disney['Volatility'] = disney['Daily Return'].rolling(window = 10).std()

# Since we have added the Daily Return and Volatility columns, we need to account for missing values we have unintentionally
# created. It is expected that the Daily Returns column should have one missing value, and that is the percent change value
# of the first observation, as there would be no percentage change from the first observation. For the Volatility variable,
# the first ten observations are expected to be missing since no 10-day rolling standard deviation can be established prior
# to ten past observations. I will fix this by inputting zeros for these missing values using fillna().

disney.fillna(0, inplace = True)
```

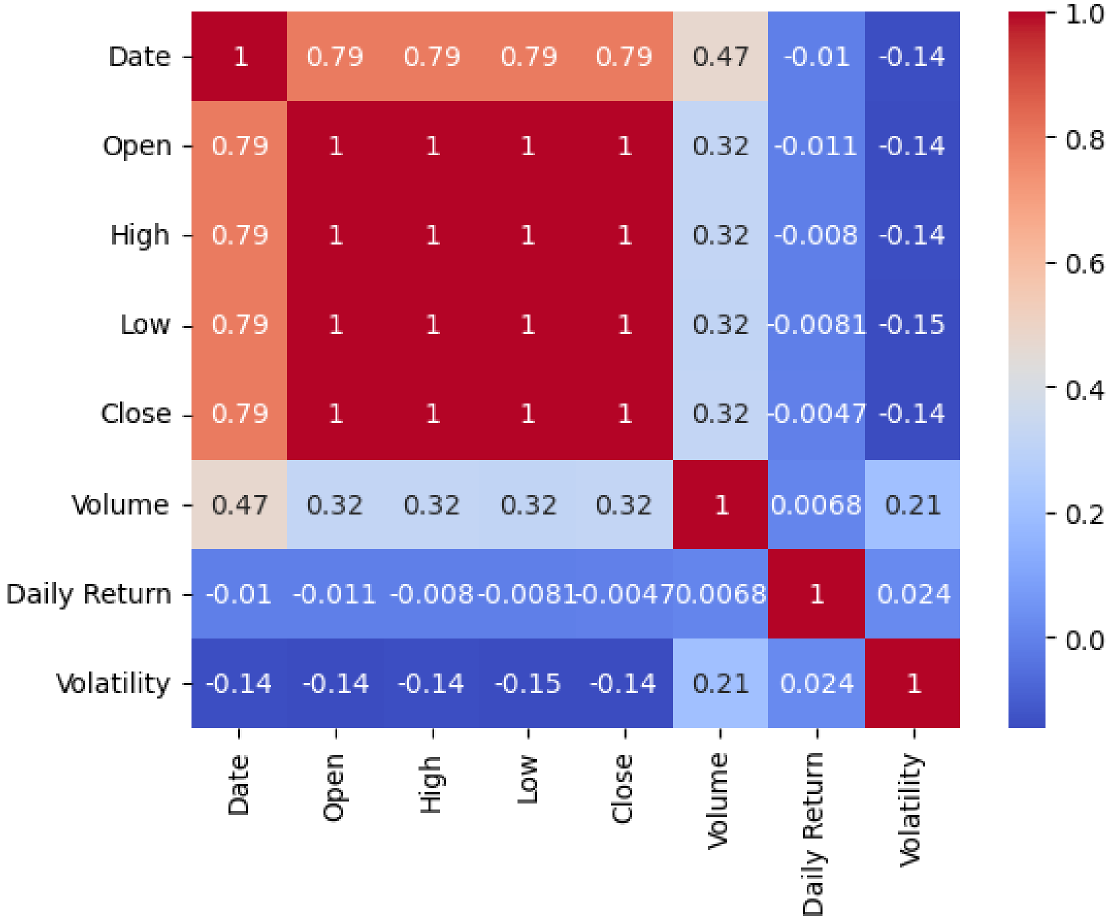
```python
# I will print the dataset to show the missing values filled in as
well as the Daily Returns and Volatility columns.

disney.head(30)
```

```
          Date      Open      High       Low     Close     Volume  \
0  1962-01-02  0.057941  0.059886  0.057941  0.057941   841958.0   
1  1962-01-03  0.057941  0.058914  0.057941  0.058719   801865.0   
2  1962-01-04  0.058719  0.058914  0.058331  0.058719   962238.0   
3  1962-01-05  0.058719  0.059108  0.058525  0.058914   962238.0   
4  1962-01-08  0.058914  0.059691  0.057553  0.058719  1282984.0   
5  1962-01-09  0.058719  0.059886  0.058331  0.059886   641492.0   
6  1962-01-10  0.059886  0.060858  0.059886  0.060469   681585.0   
7  1962-01-11  0.060469  0.062608  0.060275  0.062219  2004663.0   
8  1962-01-12  0.062219  0.062414  0.059497  0.060275  2004663.0   
9  1962-01-15  0.060275  0.060664  0.059886  0.060275   641492.0   
10 1962-01-16  0.059886  0.059886  0.058331  0.058719   360839.0   
11 1962-01-17  0.058719  0.058719  0.056775  0.056775   400933.0   
12 1962-01-18  0.057164  0.058331  0.057164  0.057941   320746.0   
13 1962-01-19  0.058331  0.059108  0.058331  0.059108   441026.0   
14 1962-01-22  0.059497  0.060081  0.059497  0.060081   360839.0   
15 1962-01-23  0.060081  0.061441  0.059497  0.059886  1202798.0   
16 1962-01-24  0.059886  0.059886  0.058331  0.059108   360839.0   
17 1962-01-25  0.059108  0.059303  0.058331  0.058331   160373.0   
18 1962-01-26  0.058331  0.059108  0.057941  0.057941   360839.0   
19 1962-01-29  0.057941  0.058719  0.057941  0.057941   240560.0   
20 1962-01-30  0.057941  0.058525  0.057553  0.058331   681585.0   
21 1962-01-31  0.058331  0.058525  0.057941  0.058331   320746.0   
22 1962-02-01  0.058331  0.060081  0.058331  0.059108  1282984.0   
23 1962-02-02  0.059108  0.059886  0.059108  0.059108   641492.0   
24 1962-02-05  0.059108  0.059691  0.059108  0.059108   400933.0   
25 1962-02-06  0.059108  0.059497  0.058719  0.058719   240560.0   
26 1962-02-07  0.059108  0.059886  0.059108  0.059497  1403264.0   
27 1962-02-08  0.060275  0.061636  0.060275  0.061053  2084849.0   
28 1962-02-09  0.061247  0.061830  0.061247  0.061441  1042425.0   
29 1962-02-12  0.061441  0.061636  0.061053  0.061441   641492.0   

    Daily Return  Volatility  
0       0.000000    0.000000  
1       0.013422    0.000000  
2       0.000000    0.000000  
3       0.003314    0.000000  
4      -0.003303    0.000000  
5       0.019872    0.000000  
6       0.009737    0.000000  
7       0.028939    0.000000  
8      -0.031243    0.000000  
9       0.000000    0.000000  
10     -0.025815    0.018707  
```

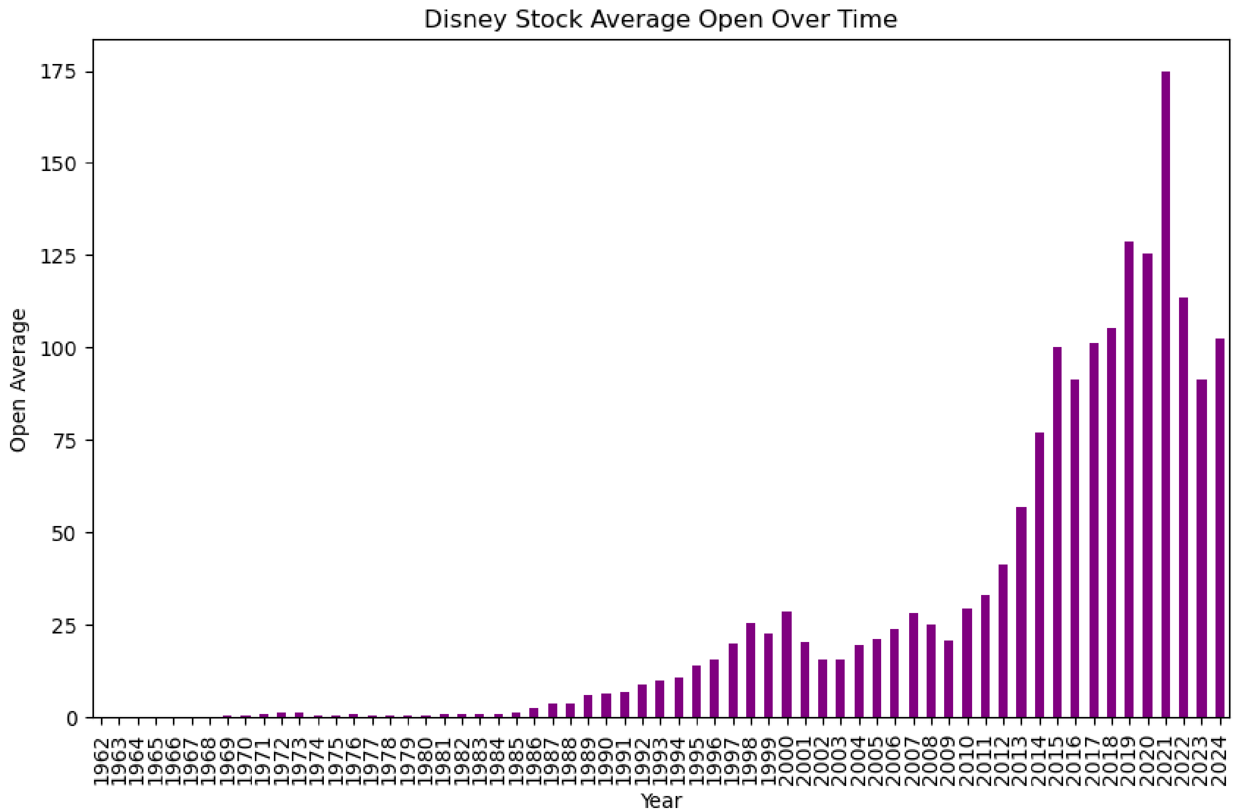
```
11     -0.033105    0.021049
12      0.020541    0.022354
13      0.020138    0.023335
14      0.016449    0.023801
15     -0.003239    0.023043
16     -0.012986    0.023122
17     -0.013157    0.020546
18     -0.006672    0.018601
19      0.000000    0.018601
20      0.006716    0.017104
21      0.000000    0.012748
22      0.013332    0.011801
23      0.000000    0.009945
24      0.000000    0.008124
25     -0.006584    0.008266
26      0.013255    0.008529
27      0.026142    0.010309
28      0.006364    0.009516
29      0.000000    0.009516

# Now that volatility has been defined, I will plot this variable over
time as well with a line chart.

plt.plot(disney['Date'], disney['Volatility'], color = 'red')
plt.title('Disney Stock Volatility Over Time')
plt.xlabel('Date')
plt.ylabel('10-Day Rolling Volatility')

plt.show()
```

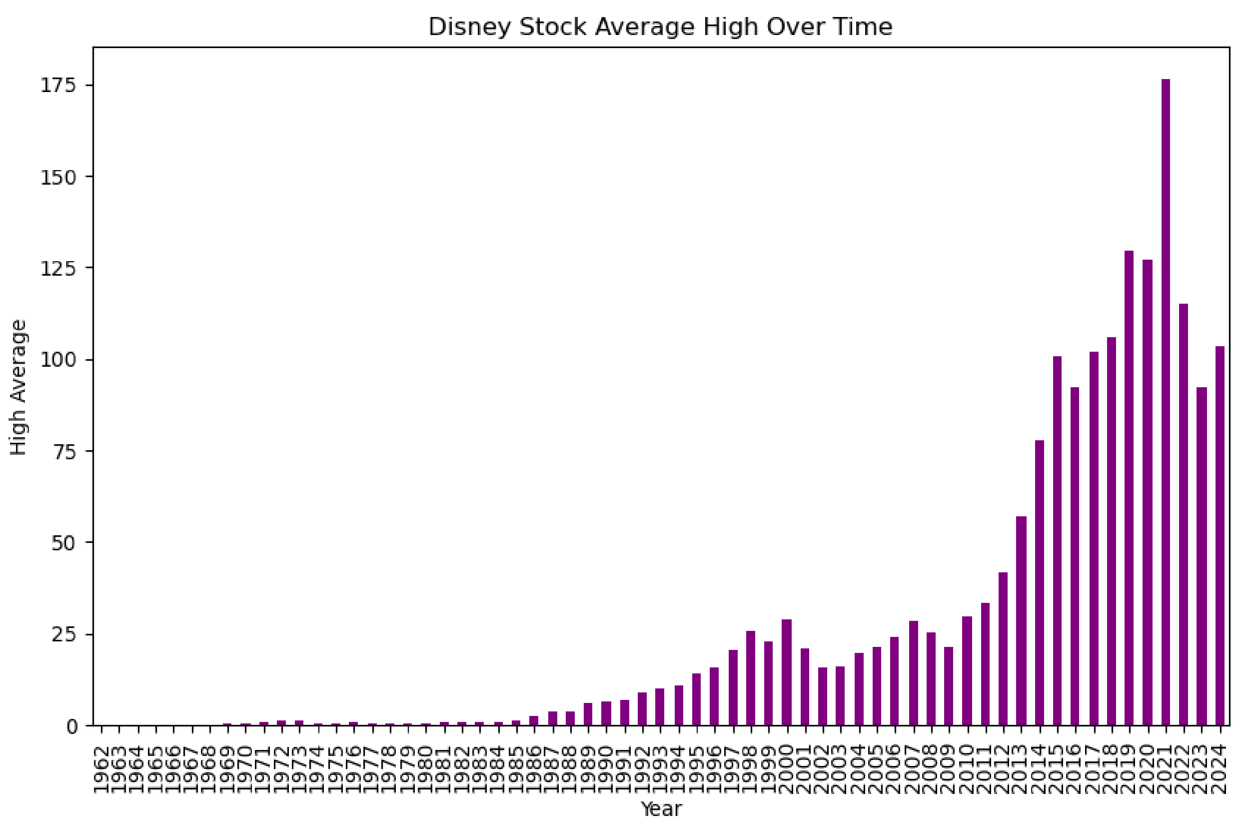


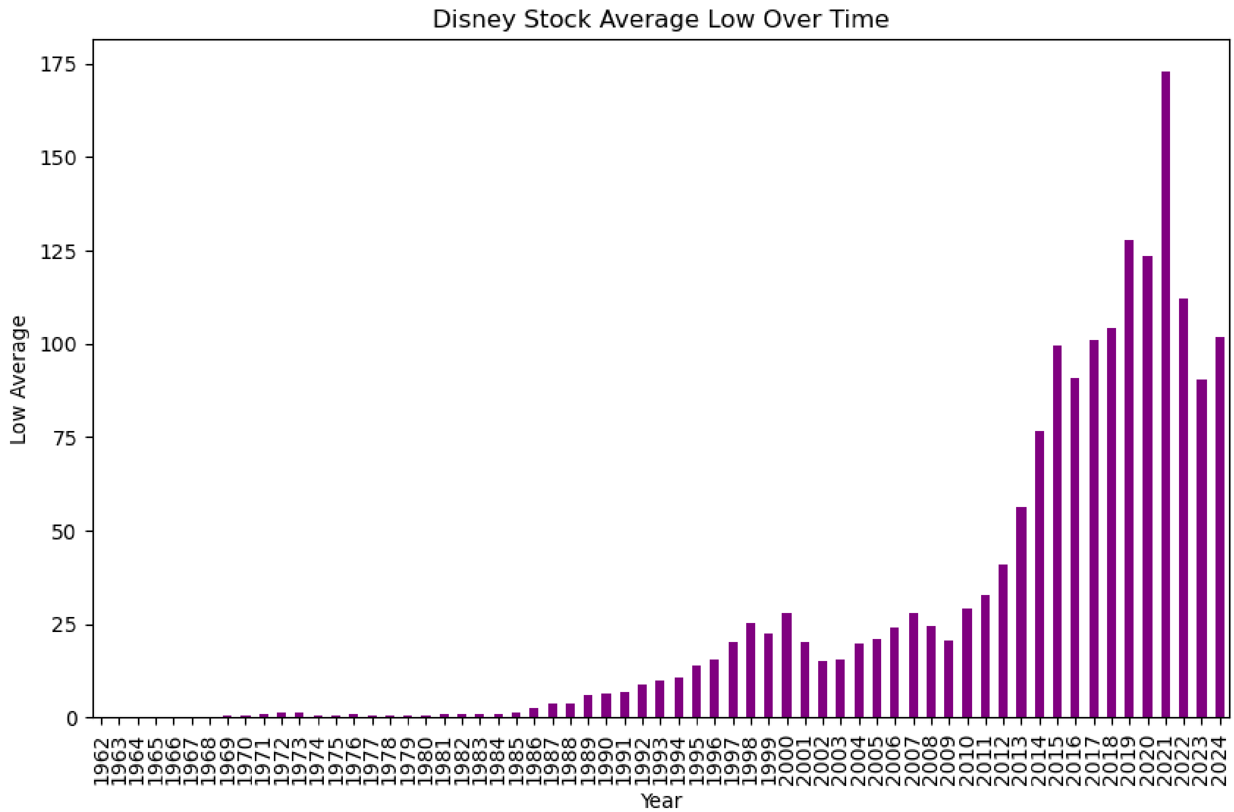

```
# Next, I will craft a heatmap that visualizes the correlation between
my outcome variable of closing stock price (Close)
# and the other variables within the dataset. This can be accomplished
using Seaborn's heatmap() function.

sns.heatmap(disney.corr(), annot = True, cmap = 'coolwarm')
plt.show()
```

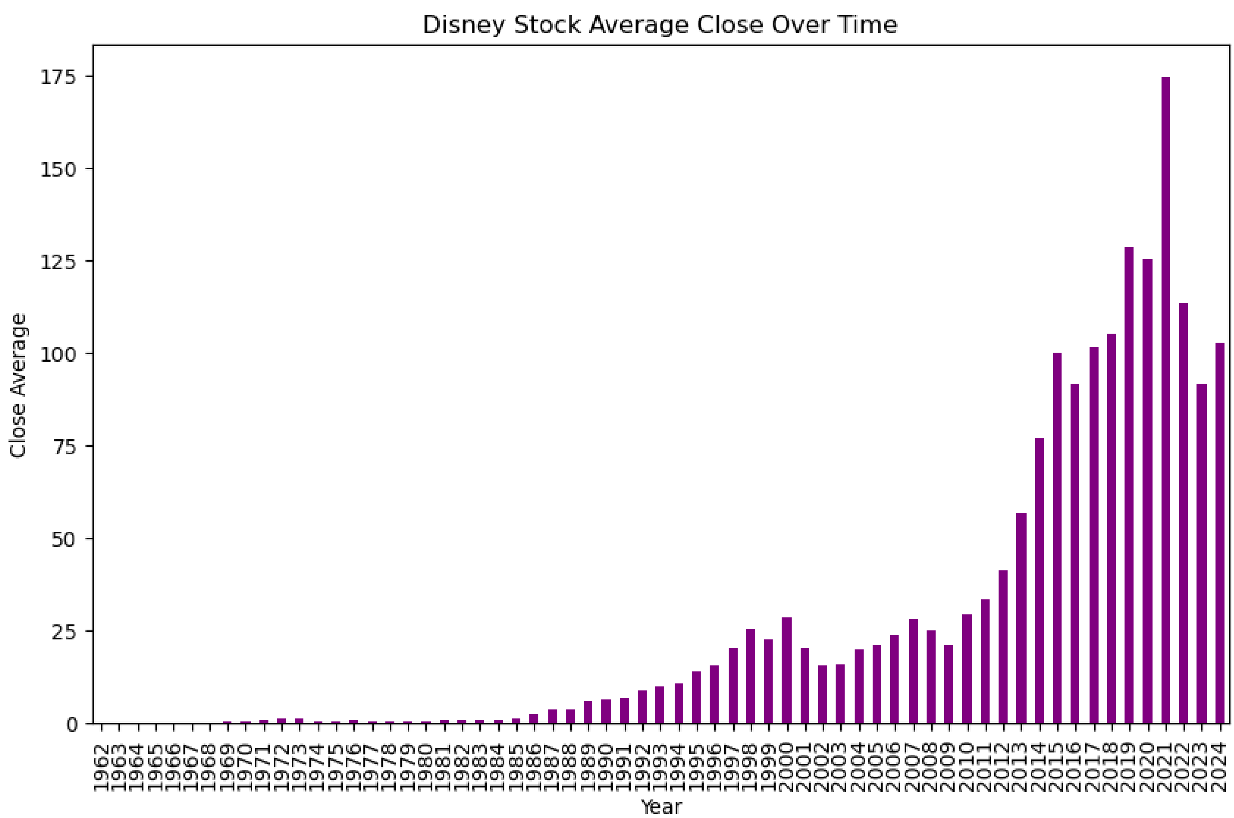


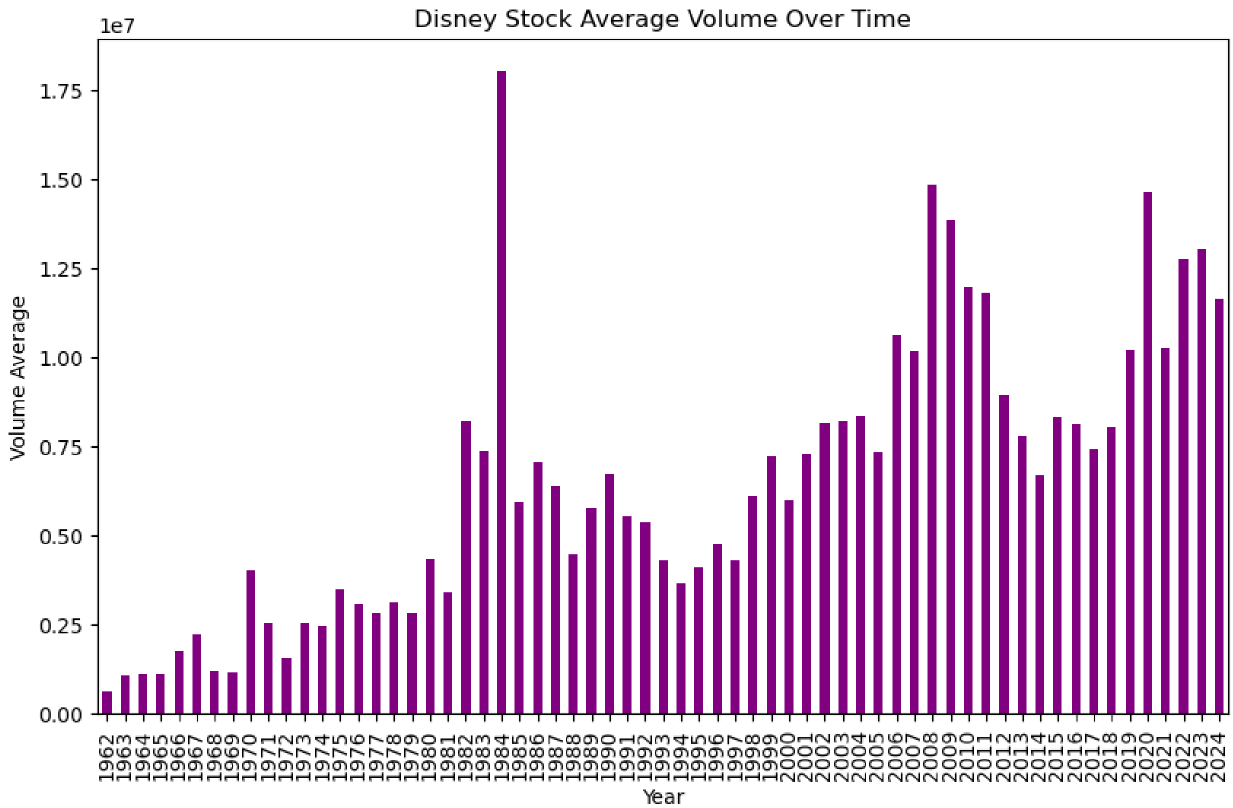

```
# To finalize my EDA, I will plot the variables within the dataset
based on their yearly averages after grouping the data by
# the year and the specified column. This will be done by employing
bar charts and another for loop that iterates through
# each variable. Visualizing these charts will allow us to see the
stock prices over the years and view which years had the
# highest and lowest variable averages.

disney['Year'] = disney['Date'].dt.year

for col in disney.drop(['Date', 'Year'], axis = 1).columns:
    yearly_avg = disney.groupby('Year')[col].mean()
    plt.figure(figsize = (10,6))
    yearly_avg.plot(kind = 'bar', color = 'purple')
    plt.title(f'Disney Stock Average {col} Over Time')
    plt.xlabel('Year')
    plt.ylabel(f'{col} Average')
    plt.show()
```


Disney Stock Average Open Over Time
Open Average
Year


Disney Stock Average High Over Time
High Average
Year


Disney Stock Average Low Over Time
Low Average
Year


Disney Stock Average Close Over Time
Close Average
Year


Disney Stock Average Volume Over Time
1e7
Volume Average
Year
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1962
1963
1964
1965
1966
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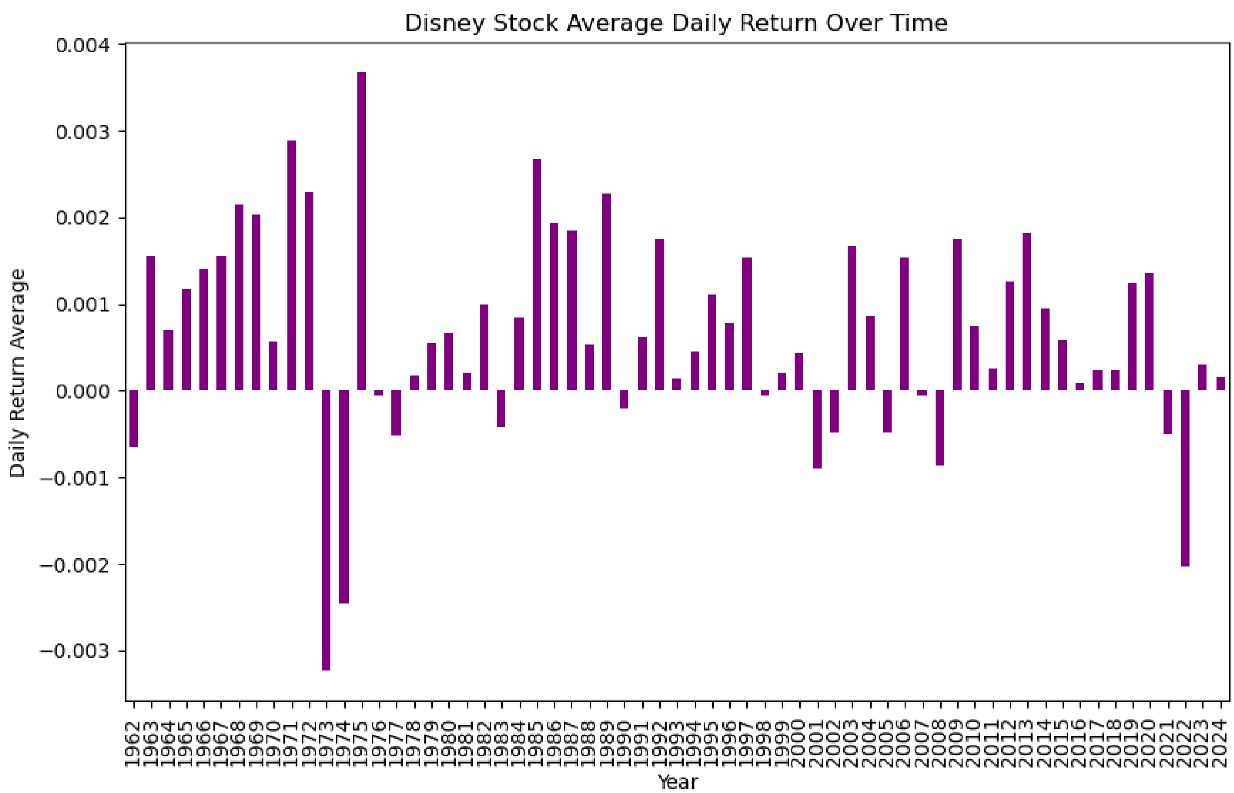
2024


Disney Stock Average Daily Return Over Time
Daily Return Average
Year
0.004
0.003
0.002
0.001
0.000
−0.001
−0.002
−0.003
1962
1963
1964
1965
1966
1967
1968
1969
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1983
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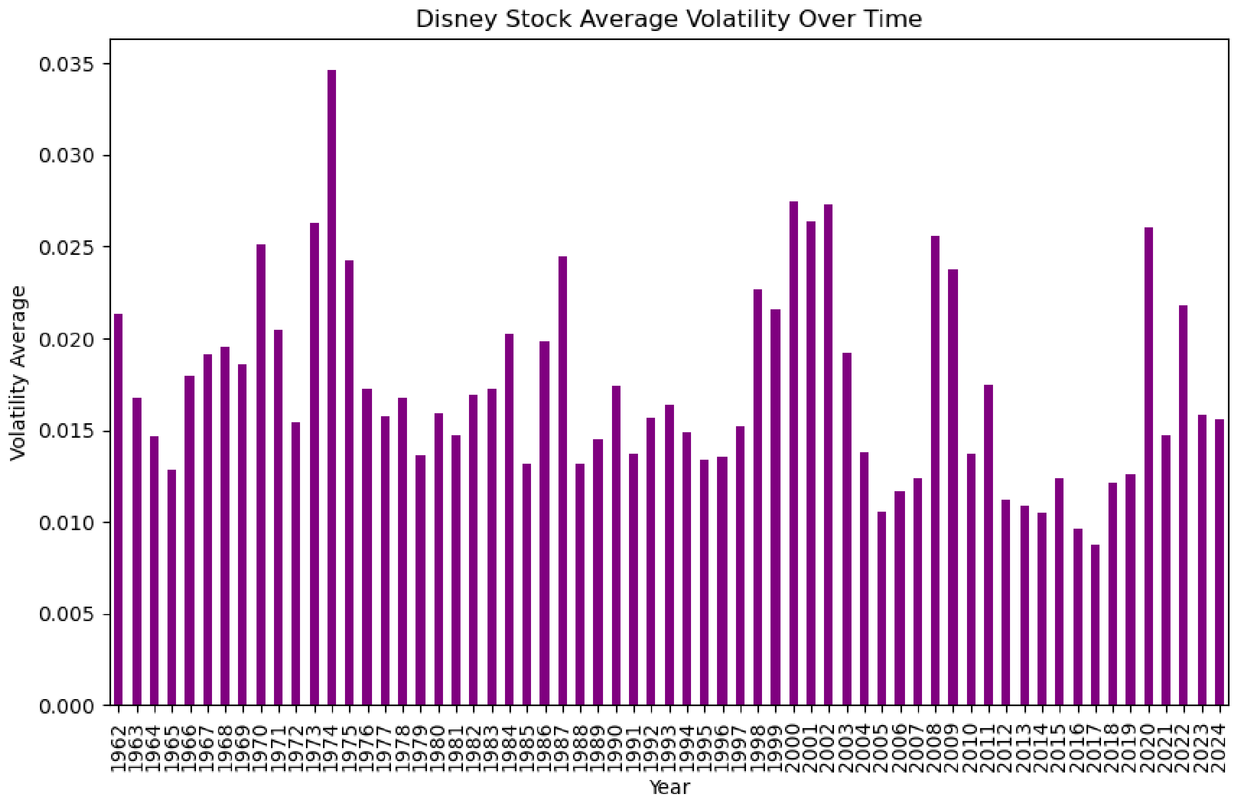
2023
2024



Training and Test Set Split and Model Creation

```
# Before I craft my initial model choice, that being the ARIMA model,
I need to perform the Augmented Dickey-Fuller (ADF)
# test on the Close outcome variable. This will test whether the data
is stationary and whether the data requires
# differencing to become stationary. To do this, I will first set the
index of the dataset to be the dates, then I will
# extract the Close variable to perform the ADF test. The ADF test
will be conducted using the adfuller() function.
# After looking at the trends uncovered during the EDA phase, I have
decided to subset the data to only include the most
# recent ten years (starting from the beginning of 2015) of stock
price data. As Disney's stock price has increased
# drastically from its initial public offering (IPO) price, the ARIMA
model will not handle the outlier data points that
# belong to the first few decades listed in the dataset.

disney.set_index('Date', inplace = True)

close_prices = disney['Close']

disney_2015_close = close_prices[close_prices.index >= '2015-01-01']

result = adfuller(disney_2015_close)
print('ADF Statistic: %f' % result[0])
```

```
print('p-value: %f' % result[1])

if result[1] > 0.05:
    print("The series is not stationary and differencing is
required.")
else:
    print("The series is stationary.")
```

```
ADF Statistic: -1.960204
p-value: 0.304290
The series is not stationary and differencing is required.
```

```
# Now that I know the data needs to be differenced, I can address that
when crafting the model and proceed with splitting
# the remaining data into training and test sets. As the data we are
dealing with is time series data, the typical
# train_test_split() function doesn't support this kind of data. So I
will manually split the data into their respective
# sets by indexing to achieve the 80/20 data split that is typical of
data science projects.

close_split = int(len(disney_2015_close) * 0.8)
close_train, close_test = disney_2015_close.iloc[:close_split],
disney_2015_close.iloc[close_split:]

# To verify that the split has been successful in its ratio of
observations, I will print the shapes of each set.

print('The size of the dataset prior to being split is:',
disney_2015_close.shape[0])
print('The size of the training dataset after being split is:',
close_train.shape[0])
print('The size of the test dataset after being split is:',
close_test.shape[0])
```

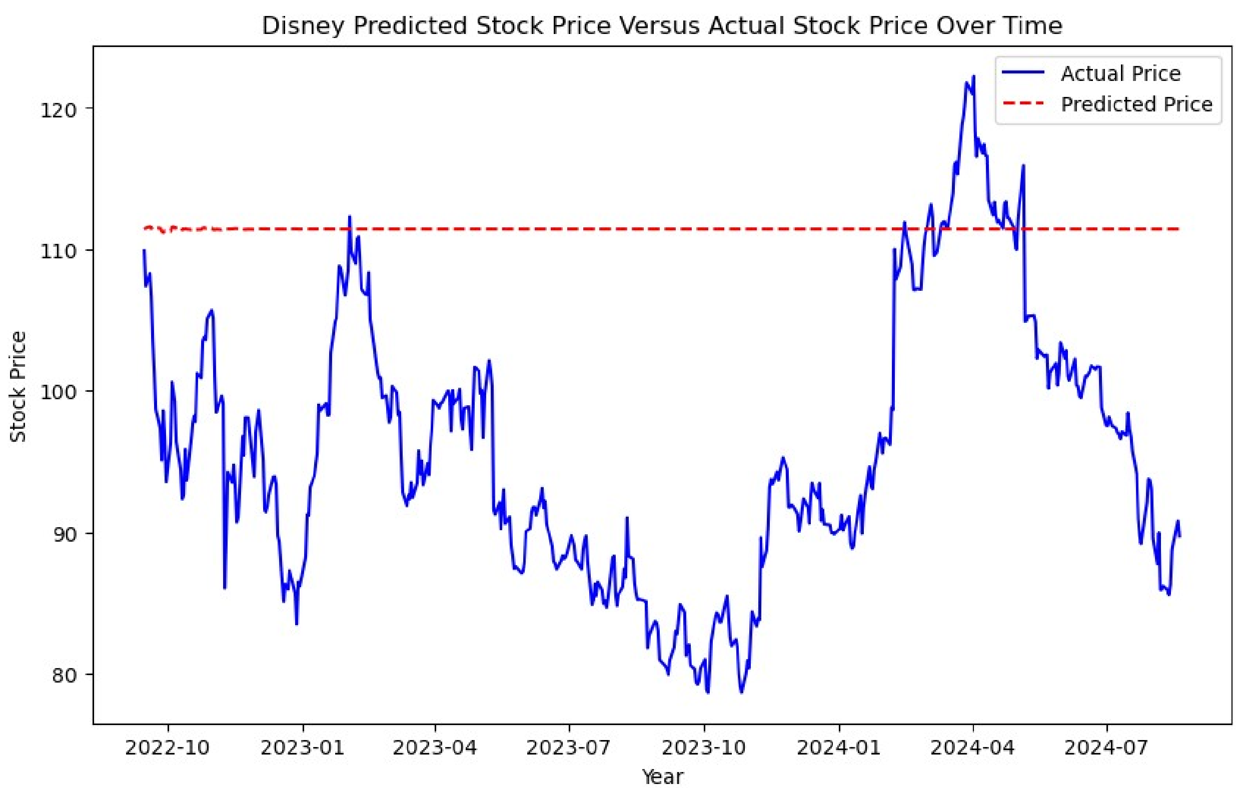
```
The size of the dataset prior to being split is: 2424
The size of the training dataset after being split is: 1939
The size of the test dataset after being split is: 485
```

```
# After seeing that the data needs to be differenced to become
stationary, I can use the auto_arima() to help determine the
# number of times the data needs to be differenced to achieve
stationarity. The helpful thing about the auto_arima()
# function is that it has a built-in grid search that optimizes the
other parameters to output the best performing ARIMA
# model. So in addition to finding the best value for d, the
differencing factor, this function also finds the best lag
# order (p) value and the best moving average order (q) value.

disney_close_model = auto_arima(close_train, seasonal = True, m = 5,
trace = True,
```

```
                                suppress_warnings = True, stepwise =
True, information_criterion = 'aic', n_jobs = -1)

print(disney_close_model.summary())

Performing stepwise search to minimize aic
 ARIMA(2,1,2)(1,0,1)[5] intercept   : AIC=8376.553, Time=7.26 sec
 ARIMA(0,1,0)(0,0,0)[5] intercept   : AIC=8376.994, Time=0.13 sec
 ARIMA(1,1,0)(1,0,0)[5] intercept   : AIC=8374.051, Time=0.68 sec
 ARIMA(0,1,1)(0,0,1)[5] intercept   : AIC=8374.255, Time=0.74 sec
 ARIMA(0,1,0)(0,0,0)[5]             : AIC=8375.067, Time=0.13 sec
 ARIMA(1,1,0)(0,0,0)[5] intercept   : AIC=8372.057, Time=0.36 sec
 ARIMA(1,1,0)(0,0,1)[5] intercept   : AIC=8374.052, Time=0.67 sec
 ARIMA(1,1,0)(1,0,1)[5] intercept   : AIC=8371.224, Time=3.27 sec
 ARIMA(1,1,0)(2,0,1)[5] intercept   : AIC=8370.567, Time=2.19 sec
 ARIMA(1,1,0)(2,0,0)[5] intercept   : AIC=8371.330, Time=0.84 sec
 ARIMA(1,1,0)(2,0,2)[5] intercept   : AIC=8369.101, Time=4.34 sec
 ARIMA(1,1,0)(1,0,2)[5] intercept   : AIC=8370.006, Time=2.46 sec
 ARIMA(0,1,0)(2,0,2)[5] intercept   : AIC=8375.573, Time=4.95 sec
 ARIMA(2,1,0)(2,0,2)[5] intercept   : AIC=8370.847, Time=5.40 sec
 ARIMA(1,1,1)(2,0,2)[5] intercept   : AIC=8370.840, Time=7.48 sec
 ARIMA(0,1,1)(2,0,2)[5] intercept   : AIC=8369.325, Time=6.94 sec
 ARIMA(2,1,1)(2,0,2)[5] intercept   : AIC=8372.853, Time=8.42 sec
 ARIMA(1,1,0)(2,0,2)[5]             : AIC=8367.181, Time=2.17 sec
 ARIMA(1,1,0)(1,0,2)[5]             : AIC=8368.082, Time=1.07 sec
 ARIMA(1,1,0)(2,0,1)[5]             : AIC=8368.643, Time=1.09 sec
 ARIMA(1,1,0)(1,0,1)[5]             : AIC=inf, Time=1.79 sec
 ARIMA(0,1,0)(2,0,2)[5]             : AIC=8373.643, Time=1.77 sec
 ARIMA(2,1,0)(2,0,2)[5]             : AIC=8368.925, Time=2.61 sec
 ARIMA(1,1,1)(2,0,2)[5]             : AIC=8368.918, Time=2.74 sec
 ARIMA(0,1,1)(2,0,2)[5]             : AIC=8367.405, Time=2.27 sec
 ARIMA(2,1,1)(2,0,2)[5]             : AIC=8370.931, Time=2.92 sec

Best model:  ARIMA(1,1,0)(2,0,2)[5]
Total fit time: 74.765 seconds
                               SARIMAX Results

======================================================================
========================
Dep. Variable:                                      y   No.
Observations:                 1939
Model:             SARIMAX(1, 1, 0)x(2, 0, [1, 2], 5)   Log Likelihood
-4177.590
Date:                                Sat, 05 Oct 2024   AIC
8367.181
Time:                                        03:35:42   BIC
8400.597
Sample:                                             0   HQIC
8379.470
                                               - 1939
```

```
Covariance Type:                                  opg

======================================================================
========
                  coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
ar.L1          -0.0664      0.014     -4.853      0.000      -0.093
-0.040
ar.S.L5        -1.0476      0.189     -5.529      0.000      -1.419
-0.676
ar.S.L10       -0.6049      0.158     -3.840      0.000      -0.914
-0.296
ma.S.L5         1.0464      0.184      5.696      0.000       0.686
1.406
ma.S.L10        0.6498      0.148      4.401      0.000       0.360
0.939
sigma2          4.3635      0.053     82.969      0.000       4.260
4.467
======================================================================
=============
Ljung-Box (L1) (Q):                  0.00   Jarque-Bera (JB):
12864.26
Prob(Q):                             0.98   Prob(JB):
0.00
Heteroskedasticity (H):              7.11   Skew:
0.67
Prob(H) (two-sided):                 0.00   Kurtosis:
15.55
======================================================================
=============

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

# Now that we have our model, which turned out to be a SARIMAX model
instead of my chosen ARIMA model due to the presence of
# seasonality within the data (as shown in some of the charts
displayed in the EDA stage), we can craft our predictions to
# realize the Root Mean Squared Error (RMSE) statistic, which will
identify how much variance within the data is explained
# by the model.

predictions = disney_close_model.predict(n_periods = len(close_test))

disney_close_rmse = np.sqrt(mean_squared_error(close_test,
```

```
predictions))
print('The RMSE of the SARIMAX model is', disney_close_rmse)

The RMSE of the SARIMAX model is 18.241334161337864

# Now while the RMSE shows the overall margin of error between the
model's predictions and the actual values, I would like
# to see the predictions plotted over time against the test values.
Upon creating a line chart showcasing both sets of
# values, we can visually see whether the predictions mirror the test
value closely.

plt.figure(figsize = (10,6))
plt.plot(close_test.index, close_test.values, label = 'Actual Price',
color = 'blue')
plt.plot(close_test.index, predictions.values, label = 'Predicted
Price', color = 'red', linestyle='--')

plt.title('Disney Predicted Stock Price Versus Actual Stock Price Over
Time')
plt.xlabel('Year')
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```



With both the RMSE statistic and the prediction line chart highlighting an underwhelming performance from the SARIMAX model, I will be moving forward with the creation of a random forest regressor model. I believe that the random forest regressor may be able to take more variables under consideration than the SARIMAX model as the entirety of the dataset can be used to train the model as opposed to only the outcome Close variable. Should the random forest regressor perform poorly as well, I will revisit the auto_arima() function to output a SARIMAX model that will be able to handle the other external variables as well.

```
# To create the random forest regressor, I will need to resplit the
data using the same ratio, yet I will use
# train_test_split() to do so. To do this though, as the random forest
algorithm isn't equipped to handle time series data
# naturally, I will be adding lagged values to the dataset so the
algorithm can learn that the past observations affect the
# future values. I will input five lagged value variables (one trading
week's worth of stock prices) based on the Close
# variable and then I will drop the rows containing missing values.

for i in range(1, 6):
    disney[f'Lag {i}'] = disney['Close'].shift(i)

# To provide the random forest regressor with more features that could
potentiall increase the algorithm's accuracy in
# predicting future Disney stock price, I will add even more features
to the dataset, specifically moving averages
# (3, 5, and 10-day) for both the Close variable and the Volume
variables.

disney['Three Day Close Rolling Mean'] =
disney['Close'].rolling(window = 3).mean()
disney['Five Day Close Rolling Mean'] = disney['Close'].rolling(window
= 5).mean()
disney['Ten Day Close Rolling Mean'] = disney['Close'].rolling(window
= 10).mean()

disney['Three Day Volume Rolling Mean'] =
disney['Volume'].rolling(window = 3).mean()
disney['Five Day Volume Rolling Mean'] =
disney['Volume'].rolling(window = 5).mean()
disney['Ten Day Volume Rolling Mean'] =
disney['Volume'].rolling(window = 10).mean()

disney.dropna(inplace = True)

disney_x = disney.drop('Close', axis = 1)
disney_2015_x = disney_x[disney_x.index >= '2015-01-01']
disney_y = disney['Close']
disney_2015_y = disney_y[disney_y.index >= '2015-01-01']

# For time series data, the order in which the observations take place
```

```
is important, so I will set the shuffle argument to
# False so I can split the data so as to keep the most recent
observations within the test set and the oldest observations
# in the training set.

close_xtrain, close_xtest, close_ytrain, close_ytest =
train_test_split(disney_2015_x, disney_2015_y, test_size = 0.2,

shuffle = False)

random_forest_close_model = RandomForestRegressor(n_estimators = 100,
random_state = 123)
random_forest_close_model.fit(close_xtrain, close_ytrain)
```

```
RandomForestRegressor(random_state=123)
```

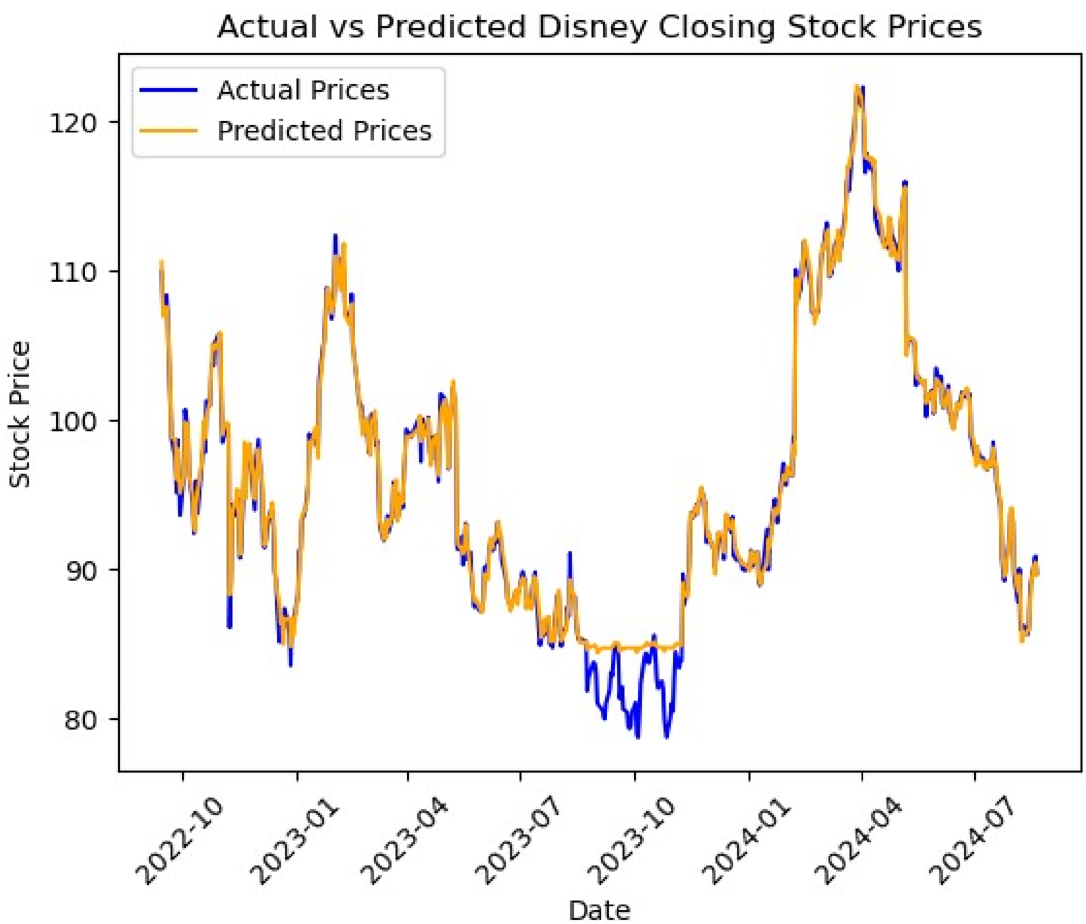
```
# Now that the model has been crafted, I will output its performance
metrics (RMSE and R-Squared).

rf_predictions = random_forest_close_model.predict(close_xtest)

rf_close_rmse = np.sqrt(mean_squared_error(close_ytest,
rf_predictions))
rf_close_r2 = r2_score(close_ytest, rf_predictions)

print('The RMSE of the random forest regressor model is',
rf_close_rmse)
print('The R-Squared value of the random forest regressor model is',
rf_close_r2)
```

```
The RMSE of the random forest regressor model is 1.2401795293864457
The R-Squared value of the random forest regressor model is
0.9830673332570158
```

Upon seeing the performance metrics for the random forest algorithm, it can be seen that not only does the model perform better than the SARIMAX model's output based on the RMSE, but the fact that the R-Squared is over 0.98 indicates that the model is a good fit for the data as over 98% of the variance within the data can be explained by the model. I will output a visualization showcasing predicted versus actual values for this model as well to make sure that the random forest regressor does indeed closely mirror the true stock prices over time.

```
# The line plot that will confirm whether the predictions closely
resemble Disney's actual stock prices is created here.

plt.plot(close_ytest.index, close_ytest, label = 'Actual Prices',
color = 'blue')
plt.plot(close_ytest.index, rf_predictions, label = 'Predicted
Prices', color = 'orange')
plt.title('Actual vs Predicted Disney Closing Stock Prices')
plt.xlabel('Date')
```

```
plt.xticks(rotation = 45)
plt.ylabel('Stock Price')
plt.legend()
plt.show()
```




```
# With the confirmation that the random forest regressor model has done well in predicting Disney stock price, I'd like to
# go a step further and have the model output predictions for observations beyond the dataset's observations, which would
# mean that the model needs to predict Disney's stock price past August 20, 2024. To accomplish this, I need to create a
# DataFrame that houses data similar to the dataset we have already at our disposal. I will create a date range variable
# that starts on August 21, 2024 and ends 25 business days from that date (September 2nd cannot be included due to Labor Day
# being an observed federal holiday with the stock market closed).

future_dates = pd.date_range(start = '2024-08-21', periods = 26, freq = 'B').difference([pd.Timestamp('2024-09-02')])
```

```
# I will create the DataFrame that will hold these dates and will have
the other features seen in our previous dataset added
# in to mimic real data observations.

future_data = pd.DataFrame(index = future_dates)

# To add the variables seen in the Kaggle dataset along with the
features I have engineered, I will extract the last data
# point from every feature, add a random small change with the help of
np.random.normal() and make that new feature column
# the same size as the future dates series that was created earlier.
The only feature that will not have the slight
# numerical variation is the Year column since it is meant to be a
string value. The small numerical change has been added
# to simulate real-world stock variability and to prevent the
inputation of uniform observations.

future_data['Open'] = disney_2015_x['Open'].iloc[-1] * (1 +
np.random.normal(0, 0.01, size = len(future_data)))
future_data['High'] = disney_2015_x['High'].iloc[-1] * (1 +
np.random.normal(0, 0.01, size = len(future_data)))
future_data['Low'] = disney_2015_x['Low'].iloc[-1] * (1 +
np.random.normal(0, 0.01, size = len(future_data)))
future_data['Volume'] = disney_2015_x['Volume'].iloc[-1] * (1 +
np.random.normal(0, 0.01, size = len(future_data)))
future_data['Daily Return'] = disney_2015_x['Daily Return'].iloc[-1] *
(1 + np.random.normal(0, 0.01,

size = len(future_data)))
future_data['Volatility'] = disney_2015_x['Volatility'].iloc[-1] * (1
+ np.random.normal(0, 0.01, size = len(future_data)))
future_data['Year'] = disney_2015_x['Year'].iloc[-1]

# The lagged features that need to be added into the future prices
DataFrame will be derived from the disney_2015_y variable
# as the lagged features here were used to create the random forest
regressor model, so they should mirror those values. The
# same minute numerical change will be added here as well. The same
applies to the Close Rolling Mean variables.

future_data['Lag 1'] = disney_2015_y.shift(1).iloc[-1] * (1 +
np.random.normal(0, 0.01))
future_data['Lag 2'] = disney_2015_y.shift(2).iloc[-1] * (1 +
np.random.normal(0, 0.01))
future_data['Lag 3'] = disney_2015_y.shift(3).iloc[-1] * (1 +
np.random.normal(0, 0.01))
future_data['Lag 4'] = disney_2015_y.shift(4).iloc[-1] * (1 +
np.random.normal(0, 0.01))
future_data['Lag 5'] = disney_2015_y.shift(5).iloc[-1] * (1 +
np.random.normal(0, 0.01))
```

```
future_data['Three Day Close Rolling Mean'] =
disney_2015_y.rolling(3).mean().iloc[-1] * (1 + np.random.normal(0,
0.01))
future_data['Five Day Close Rolling Mean'] =
disney_2015_y.rolling(5).mean().iloc[-1] * (1 + np.random.normal(0,
0.01))
future_data['Ten Day Close Rolling Mean'] =
disney_2015_y.rolling(10).mean().iloc[-1] * (1 + np.random.normal(0,
0.01))

# For the Volume Rolling Mean features, I need to use the
disney_2015_x variable again.

future_data['Three Day Volume Rolling Mean'] =
disney_2015_x['Volume'].rolling(3).mean().iloc[-1] * (1 +

np.random.normal(0,

0.01))
future_data['Five Day Volume Rolling Mean'] =
disney_2015_x['Volume'].rolling(5).mean().iloc[-1] * (1 +

np.random.normal(0,

0.01))
future_data['Ten Day Volume Rolling Mean'] =
disney_2015_x['Volume'].rolling(10).mean().iloc[-1] * (1 +

np.random.normal(0,

0.01))

# With lagged values, we have unintentionally placed NaN values within
the newm DataFrame, so I will address that by using
# fillna() with the method argument set to ffill to fill in the
missing values with the most recent values.

future_data.fillna(method = 'ffill', inplace = True)

# Now we can use the already crafted random forest regressor to
generate closing stock price predictions on the future dates
# DataFrame. I will append these predictions to the future dates
DataFrame with the purpose of plotting them against
# Disney's actual closing stock prices to see the accuracy of the
model when predicting future data points not previously
# seen.

future_predictions = random_forest_close_model.predict(future_data)
future_data['Predicted Close'] = future_predictions
```

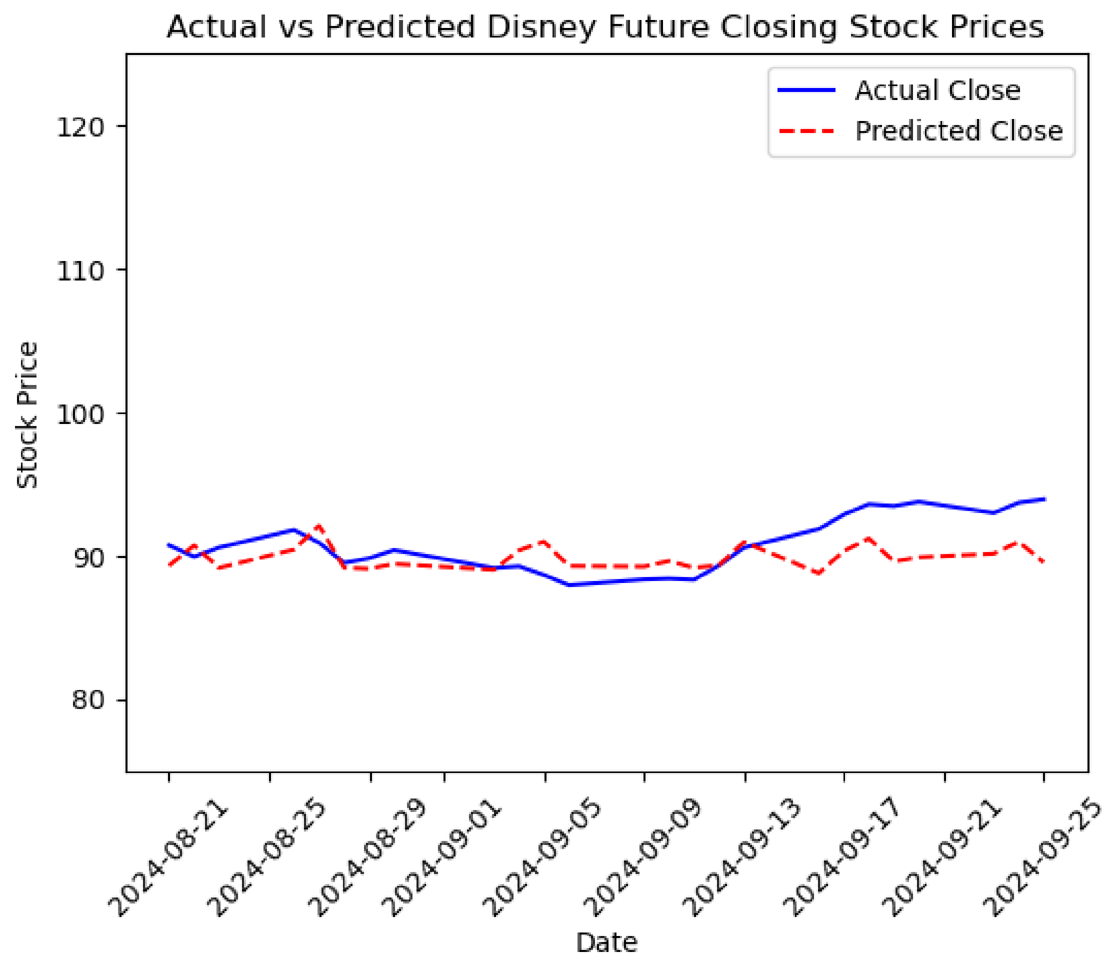
```python
# I will print the predictions created by the random forest regressor
model to verify the transformations did yield viable
# predictions.

print(future_data[['Predicted Close']])
```

```
            Predicted Close
2024-08-21        89.295834
2024-08-22        90.703388
2024-08-23        89.143961
2024-08-26        90.418614
2024-08-27        92.082521
2024-08-28        89.160118
2024-08-29        89.084600
2024-08-30        89.421222
2024-09-03        89.013669
2024-09-04        90.366047
2024-09-05        90.966788
2024-09-06        89.273477
2024-09-09        89.233557
2024-09-10        89.615670
2024-09-11        89.152077
2024-09-12        89.321634
2024-09-13        90.940140
2024-09-16        88.779018
2024-09-17        90.312578
2024-09-18        91.188166
2024-09-19        89.595049
2024-09-20        89.877185
2024-09-23        90.129895
2024-09-24        90.959336
2024-09-25        89.524706
```

```python
# After looking for the actual Disney closing stock prices for the
future dates in the dataset, I locked onto a Yahoo
# Finance link that displayed them, that link being cited here:
https://finance.yahoo.com/quote/DIS/history/

future_data['Actual Close'] = [90.72, 89.92, 90.56, 91.78, 90.90,
89.49, 89.81, 90.38, 89.13, 89.25, 88.65, 87.94, 88.34,
                               88.40, 88.32, 89.30, 90.55, 91.85,
92.86, 93.58, 93.45, 93.75, 92.97, 93.69, 93.92]

# I will print the dataset to ensure the addition of the Actual Close
column.

future_data.head()
```

```
                  Open       High        Low        Volume  Daily
Return  \
2024-08-21  90.554159  89.492234  89.074668  8.924213e+06     -
0.011977
2024-08-22  91.836553  90.572937  90.902684  8.998622e+06     -
0.011926
2024-08-23  90.415529  89.860909  88.558586  8.814206e+06     -
0.011781
2024-08-26  89.829558  90.866964  89.918191  8.742715e+06     -
0.012039
2024-08-27  91.035902  92.849770  91.357582  8.835052e+06     -
0.011965

            Volatility  Year      Lag 1      Lag 2      Lag 3      Lag
4  \
2024-08-21    0.019125  2024  92.263973  90.485351  87.540714
85.101531
2024-08-22    0.019030  2024  92.263973  90.485351  87.540714
85.101531
2024-08-23    0.019300  2024  92.263973  90.485351  87.540714
85.101531
2024-08-26    0.019444  2024  92.263973  90.485351  87.540714
85.101531
2024-08-27    0.019411  2024  92.263973  90.485351  87.540714
85.101531

                Lag 5  Three Day Close Rolling Mean  \
2024-08-21  86.129837                     91.064071
2024-08-22  86.129837                     91.064071
2024-08-23  86.129837                     91.064071
2024-08-26  86.129837                     91.064071
2024-08-27  86.129837                     91.064071

            Five Day Close Rolling Mean  Ten Day Close Rolling Mean  \
2024-08-21                    89.074001                   86.461893
2024-08-22                    89.074001                   86.461893
2024-08-23                    89.074001                   86.461893
2024-08-26                    89.074001                   86.461893
2024-08-27                    89.074001                   86.461893

            Three Day Volume Rolling Mean  Five Day Volume Rolling
Mean  \
2024-08-21                   9.650616e+06
1.011763e+07
2024-08-22                   9.650616e+06
1.011763e+07
2024-08-23                   9.650616e+06
1.011763e+07
2024-08-26                   9.650616e+06
1.011763e+07
```

```
2024-08-27                   9.650616e+06
1.011763e+07

            Ten Day Volume Rolling Mean  Predicted Close  Actual Close

2024-08-21                 1.452802e+07        89.295834         90.72

2024-08-22                 1.452802e+07        90.703388         89.92

2024-08-23                 1.452802e+07        89.143961         90.56

2024-08-26                 1.452802e+07        90.418614         91.78

2024-08-27                 1.452802e+07        92.082521         90.90


# With the actual and predicted future closing stock prices
calculated, I can calculate the new RMSE to see how small or
# large the new margin of error is.

disney_future_close_rmse =
np.sqrt(mean_squared_error(future_data['Actual Close'],
future_data['Predicted Close']))

print('The RMSE of the random forest regressor model using the future
Disney closing stock prices is',
      disney_future_close_rmse)

The RMSE of the random forest regressor model using the future Disney
closing stock prices is 2.0719174207572593

# I will now plot the predicted future observations against the actual
future observations using the same scale as the
# previous actual versus predictions plot to see how the model
performs with unseen data.

plt.plot(future_data.index, future_data['Actual Close'], label =
'Actual Close', color = 'blue')
plt.plot(future_data.index, future_data['Predicted Close'], label =
'Predicted Close', color = 'red', linestyle = '--')

plt.title('Actual vs Predicted Disney Future Closing Stock Prices')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.ylim(75, 125)
plt.xticks(rotation = 45)
plt.legend()
plt.show()
```



After seeing the random forest regressor model's performance in lieu of the SARIMAX model's substandard results, it can be said with confidence that this model is ready for deployment for specific shareholders of the Walt Disney Company. For those who wish to hold and/or buy, shareholders can see that continuing to invest in the Company is a stable investment with little fluctuation in the next 25 business days. For those wishing to sell, these shareholders can estimate how much they stand to gain or lose if they do not want to wait and are content with the potential minimal profit/loss they may face. The model also helps to reassure shareholders of Disney's strength within its business sector, allowing a potential boost in shareholder morale and more funding for the Company to continue expanding and giving back to the community and its investors.