

## ✓ Overview

Time series forecasting stock\_details\_5\_years the involves cleaning and transforming historical data, selecting models like ARIMA or Prophet, training them to capture patterns, evaluating performance using RMSE or MAE, and deploying validated models for predictions.

```
!pip install ydata-profiling
!pip install statsmodels
!pip install scikit-learn
```



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Requirement already satisfied: matplotlib>=3.5 in /usr/local/lib/python3.11/dist-packages (3.9.0)
Requirement already satisfied: pydantic>=2 in /usr/local/lib/python3.11/dist-packages (2.10.6)
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Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (2.9.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (2024.2)
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Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (2025.1.1)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-packages (0.5.6)
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Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.11/dist-packages (3.4.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (1.17.0)
```

```
Requirement already satisfied: pandas!=2.1.0,>=1.4 in /usr/local/lib/python3.11/dist-packages (1.5.3)
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Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (3.5.0)
```

```
import seaborn as sns
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from ydata_profiling import ProfileReport
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
from google.colab import drive
drive.mount('/content/drive')
```

📁 Mounted at /content/drive

```
# Import the stock_details_5_years
df = pd.read_csv("/content/drive/MyDrive/stock_details_5_years.csv")
```

```
df
```



	Date	Open	High	Low	Close	Volume	Dividends
<b>0</b>	2018-11-29 00:00:00-05:00	43.829761	43.863354	42.639594	43.083508	167080000.0	0.00
<b>1</b>	2018-11-29 00:00:00-05:00	104.769074	105.519257	103.534595	104.636131	28123200.0	0.00
<b>2</b>	2018-11-29 00:00:00-05:00	54.176498	55.007500	54.099998	54.729000	31004000.0	0.00
<b>3</b>	2018-11-29 00:00:00-05:00	83.749496	84.499496	82.616501	83.678497	132264000.0	0.00
<b>4</b>	2018-11-29 00:00:00-05:00	39.692784	40.064904	38.735195	39.037853	54917200.0	0.04
...	...	...	...	...	...	...	...
<b>67381</b>	2019-07-01 00:00:00-04:00	49.382082	49.539489	49.006054	49.521999	903800.0	0.00
<b>67382</b>	2019-07-01 00:00:00-04:00	318.700012	318.809998	310.010010	316.739990	204100.0	0.00
<b>67383</b>	2019-07-01 00:00:00-04:00	6.587493	6.604560	6.527763	6.553361	1871100.0	0.00



Next steps:

[View recommended plots](#)[New interactive sheet](#)

## ✓ Basic Metrics

```
# shape of data set
df.shape
```



(602962, 9)

```
# dataset of columns name
df.columns
```

```
Index(['Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'Dividends',
       'Stock Splits', 'Company'],
      dtype='object')
```

```
# Overview of the dataset structure
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 602962 entries, 0 to 602961
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Date                  602962 non-null object
1   Open                  602962 non-null float64
2   High                  602962 non-null float64
3   Low                   602962 non-null float64
4   Close                 602962 non-null float64
5   Volume                602962 non-null int64
6   Dividends             602962 non-null float64
7   Stock Splits          602962 non-null float64
8   Company               602962 non-null object
dtypes: float64(6), int64(1), object(2)
memory usage: 41.4+ MB
```

## ✓ Datatype Conversions

```
def date_split(x):
    a = x.split(' ')[0]
    b = x.split(' ')[1].split('-')[0]
    d = a+' '+b
    return d
```

```
pd.to_datetime(date_split(df['Date'])[0]))
```

```
Timestamp('2018-11-29 00:00:00')
```

```
df['Date'] = df['Date'].apply(lambda x:date_split(x))
df['Date']
```

```
0      2018-11-29 00:00:00
1      2018-11-29 00:00:00
2      2018-11-29 00:00:00
3      2018-11-29 00:00:00
4      2018-11-29 00:00:00
...
602957 2023-11-29 00:00:00
602958 2023-11-29 00:00:00
602959 2023-11-29 00:00:00
602960 2023-11-29 00:00:00
```

602961 2023-11-29 00:00:00

Name: Date, Length: 602962, dtype: object

df



	Date	Open	High	Low	Close	Volume	Dividends
0	2018-11-29 00:00:00	43.829761	43.863354	42.639594	43.083508	167080000	0.00
1	2018-11-29 00:00:00	104.769074	105.519257	103.534595	104.636131	28123200	0.00
2	2018-11-29 00:00:00	54.176498	55.007500	54.099998	54.729000	31004000	0.00
3	2018-11-29 00:00:00	83.749496	84.499496	82.616501	83.678497	132264000	0.00
4	2018-11-29 00:00:00	39.692784	40.064904	38.735195	39.037853	54917200	0.04
...	...	...	...	...	...	...	...
602957	2023-11-29 00:00:00	26.360001	26.397499	26.120001	26.150000	1729147	0.00
602958	2023-11-29 00:00:00	27.680000	28.535000	27.680000	28.350000	1940066	0.00
602959	2023-11-29 00:00:00	75.940002	76.555000	75.257500	75.610001	298699	0.00

## ✓ Data Cleaning

# Check for missing or null values in the stock\_details\_5\_years dataset and count them fo  
df.isna().sum()



```

Date          0
Open          0
High          0
Low           0
Close         0
Volume        0
Dividends     0
Stock Splits  0
Company       0
dtype: int64

```

## ✓ Unique Values

```
# Check the number of unique values in each column of the DataFrame 'df'
# This helps in understanding the diversity of data in each column.
df.nunique()
```

```
⇒ Date          1258
   Open         510592
   High         514315
   Low          513389
   Close        484353
   Volume       170929
   Dividends     960
   Stock Splits  40
   Company       491
   dtype: int64
```

```
value_counts = {col: df[col].value_counts() for col in ['Open', 'High', 'Low', 'Close', '
# Display the value counts for each column
for col, counts in value_counts.items():
    print(f"Value counts for {col}:\n{counts}\n")
```

```
⇒ Value counts for Open:
   Open
140.000000    55
150.000000    48
 60.000000    48
100.000000    48
 65.000000    46
      ..
 48.612281     1
161.399136     1
 28.091971     1
1171.079956     1
6164.000000     1
   Name: count, Length: 510592, dtype: int64
```

```
Value counts for High:
   High
 2.920000    36
 9.900000    29
 3.150000    29
 3.170000    28
155.000000    27
      ..
40.929012     1
440.920013     1
37.215579     1
30.501805     1
84.995003     1
   Name: count, Length: 514315, dtype: int64
```

```
Value counts for Low:
   Low
```

```
9.900000    35
3.090000    32
3.140000    28
2.890000    27
3.110000    25
..
8.793761     1
65.908869     1
84.592707     1
301.632601     1
75.257500     1
Name: count, Length: 513389, dtype: int64
```

Value counts for Close:

```
Close
2.910000    32
3.140000    30
9.950000    28
3.130000    27
9.800000    26
..
51.473606     1
124.716805     1
134.903076     1
320.975983     1
40.125000     1
```

## ✓ # Descriptive Statistics

```
# Summary statistics for numerical columns
df.describe(include = 'all').T
```



	count	unique	top	freq	mean	std	min
<b>Date</b>	602962	1258	2023-11-29 00:00:00	491	NaN	NaN	NaN
<b>Open</b>	602962.0	NaN	NaN	NaN	140.074711	275.401725	1.052425
<b>High</b>	602962.0	NaN	NaN	NaN	141.853492	279.003191	1.061195
<b>Low</b>	602962.0	NaN	NaN	NaN	138.276316	271.895276	1.026114
<b>Close</b>	602962.0	NaN	NaN	NaN	140.095204	275.477969	1.034884
<b>Volume</b>	602962.0	NaN	NaN	NaN	5895601.184909	13815961.832517	0.0
<b>Dividends</b>	602962.0	NaN	NaN	NaN	0.00731	0.12057	0.0
<b>Stock Splits</b>	602962.0	NaN	NaN	NaN	0.000344	0.050607	0.0
<b>Company</b>	602962	491	AAPL	1258	NaN	NaN	NaN

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```
# Split the data into training and test sets (e.g., last 20% for testing)
train_size = int(len(df) * 0.8)
train_data = df['Close'][:train_size]
test_data = df['Close'][train_size:]

# Fit an ARIMA model (you can adjust p, d, q based on your data)
model = ARIMA(train_data, order=(5, 1, 0)) # p=5, d=1, q=0 (adjust these values)
model_fit = model.fit()

# Make predictions for the test set
predictions = model_fit.forecast(steps=len(test_data))

# Calculate RMSE and MAE
rmse = np.sqrt(mean_squared_error(test_data, predictions))
mae = mean_absolute_error(test_data, predictions)

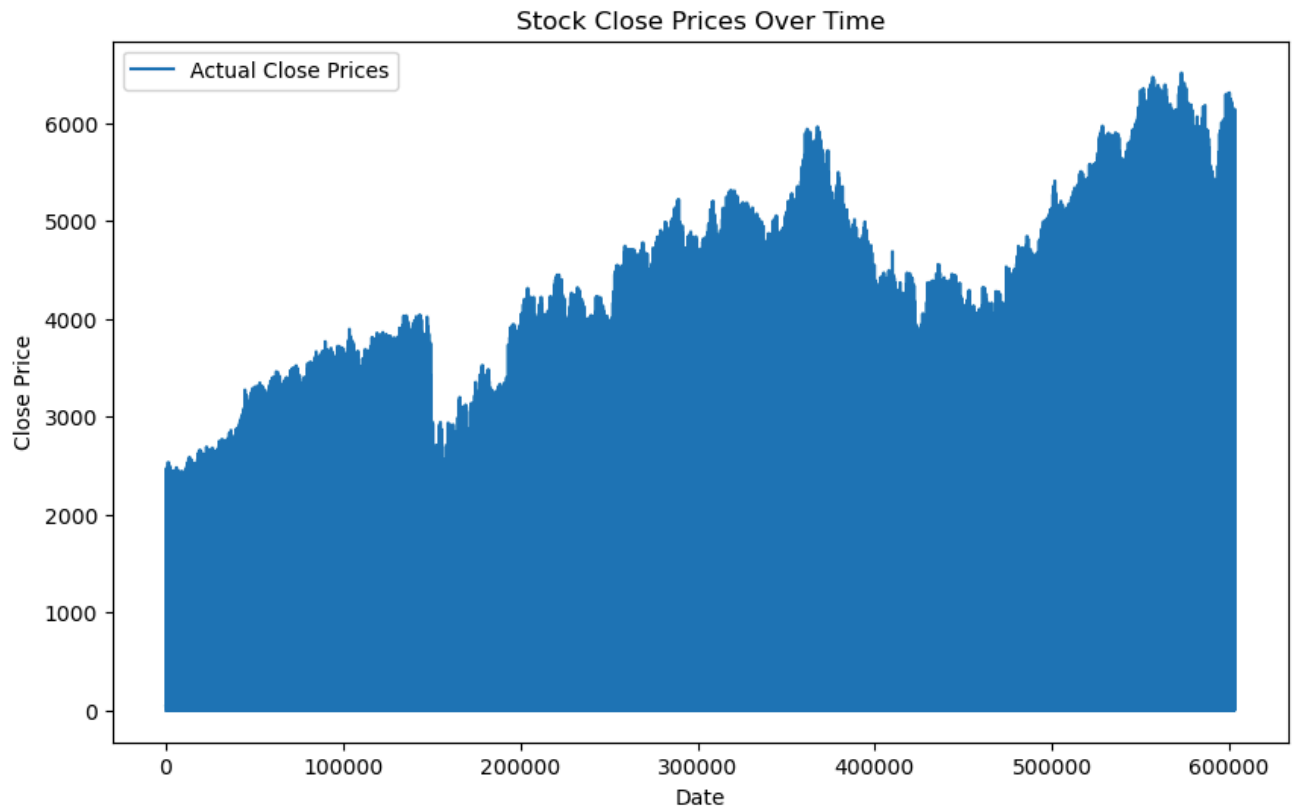
print(f"RMSE: {rmse}")
print(f"MAE: {mae}")
```

```
➡ RMSE: 354.75400438562195
   MAE: 121.07360469022312
```

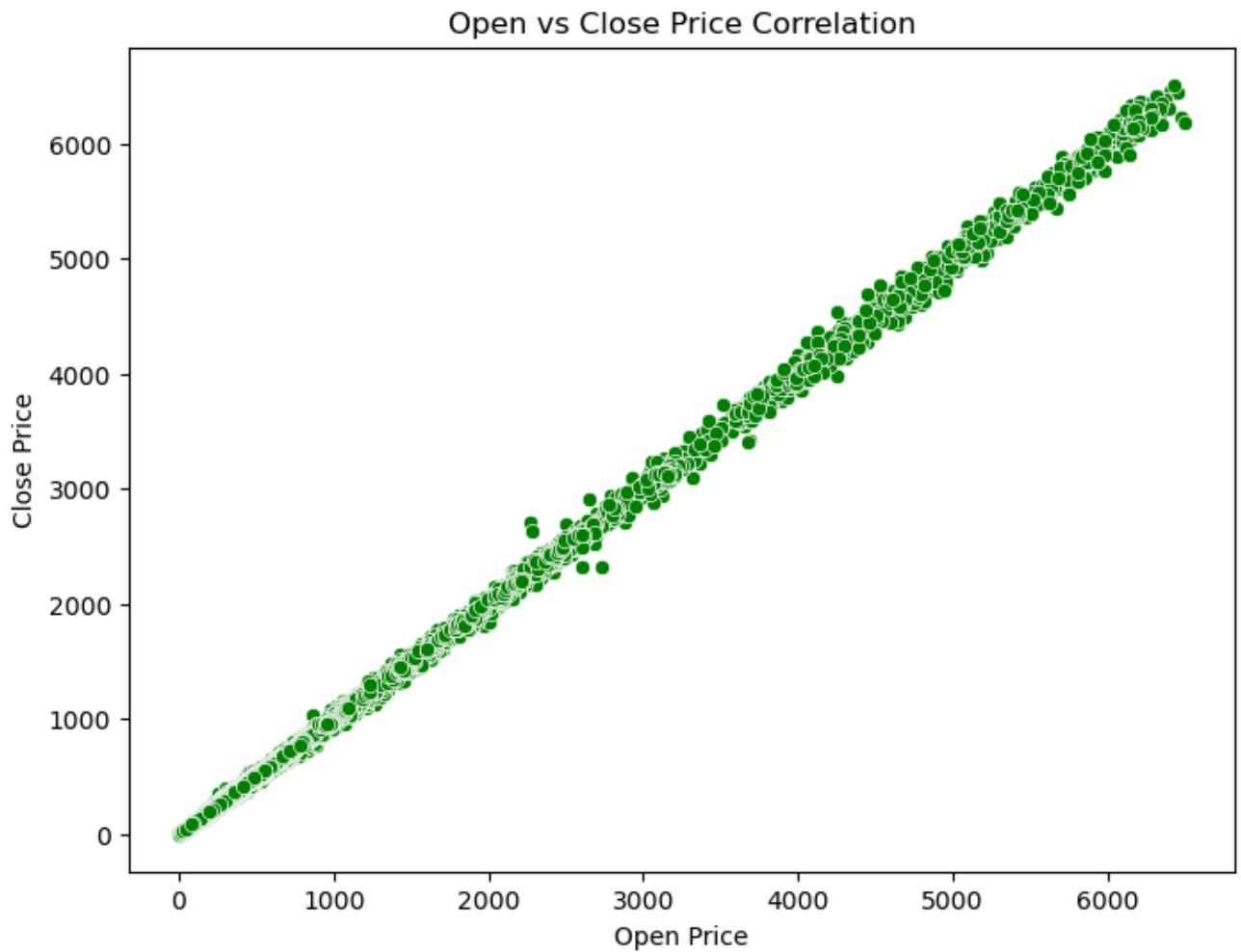
## ✓ Data Visualization

```
# 1. Plot the closing prices over time to show trends
plt.figure(figsize=(10,6))
plt.plot(df['Close'],label="Actual Close Prices")
plt.title("Stock Close Prices Over Time")
plt.xlabel("Date")
plt.ylabel("Close Price")
plt.legend()
plt.show()
```

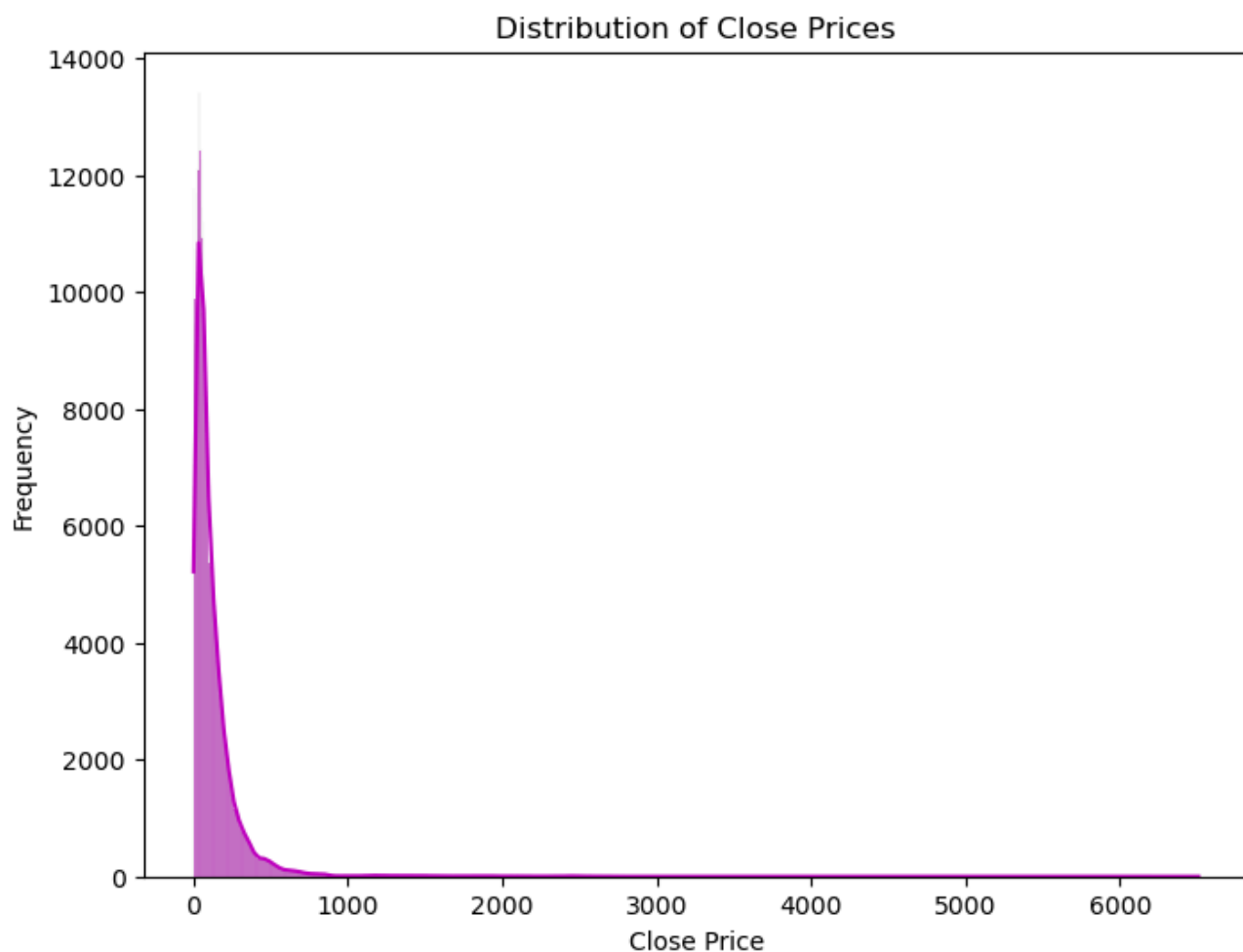




```
# 2. Correlation between Open and Close Prices ---  
plt.figure(figsize=(8,6))  
sns.scatterplot(x=data['Open'], y=data['Close'], color='green')  
plt.title('Open vs Close Price Correlation')  
plt.xlabel('Open Price')  
plt.ylabel('Close Price')  
plt.show()
```



```
# 3. Distribution of the Close Prices
plt.figure(figsize=(8,6))
sns.histplot(df['Close'], kde=True, color = 'm')
plt.title("Distribution of Close Prices")
plt.xlabel("Close Price")
plt.ylabel("Frequency")
plt.show()
```



```
# 4. Volume vs Close Prices
plt.figure(figsize=(10,6))
plt.scatter(df['Volume'],df['Close'], alpha=0.5)
plt.title("Volume vs Close Prices")
plt.xlabel("Volume")
plt.ylabel("Close Price")
plt.show()
```



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```
# Assuming 'test_data' and 'predictions' are already calculated as in your code
# Generate the corresponding date index for the test data
test_dates = df.index[train_size:] # Adjust this based on your df structure

#plot the actual vs predicted values
plt.figure(figsize=(8,6))

# plot actual test data
plt.plot(test_dates, predictions, label='Perdicted Close Prices', color='red', linestyle=

#Add title and labels
plt.title('ARIMA Model: Actual vs Predicted Close Prices', fontsize=16)
plt.xlabel("Date", fontsize=12)
plt.ylabel("Close Price", fontsize=12)

# Add legend
plt.legend()

#show grid for better readability
plt.grid(True)

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

