# **AI-Powered Stock Market Predictor**

# **Mini Project Report**

Submitted by

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## **BACHELOR OF ENGINEERING**

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# COMPUTER SCIENCE AND ENGINEERING



# St. JOSEPH'S INSTITUTE OF TECHNOLOGY (An AUTONOMOUS INSTITUTION)

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#### **AI-Powered Stock Market Predictor**

#### 1. Introduction

#### 1.1 Purpose

This report presents an analysis of stock market data using machine learning techniques, with the aim of predicting future stock prices. By examining historical stock prices, trading volumes, and external factors such as news sentiment, the goal is to develop a model that can forecast stock price trends and assist investors in making informed decisions.

#### 1.2 Scope

The project focuses on gathering and analyzing stock market data, including historical price trends, trading volumes, and relevant external factors like financial news. The analysis utilizes Python libraries such as Pandas, Matplotlib, and Scikit-learn for data processing, model development, and visualization of predictions.

### 1.3 Definitions, Acronyms, and Abbreviations

- **Matplotlib**: A Python library used for creating static, animated, and interactive visualizations, essential for presenting data insights and model results.
- **Seaborn**: A statistical data visualization library in Python, built on top of Matplotlib, used for making more sophisticated visualizations with ease.
- **Scikit-learn**: A machine learning library in Python that provides simple and efficient tools for data mining and predictive modeling, including regression and classification algorithms.
- **LSTM** (**Long Short-Term Memory**): A type of Recurrent Neural Network (RNN) that is especially effective for time-series prediction, which is crucial for forecasting stock prices based on historical data.
- **RSI** (**Relative Strength Index**): A momentum oscillator used in technical analysis to evaluate overbought or oversold conditions in a stock, often included as a feature for predictive models.

#### 1.4 Overview

This report provides an overview of the stock market prediction model, including the data collection and pre processing steps, the machine learning algorithms used for training, and the evaluation of model performance. It also highlights key findings, such as prediction accuracy, and provides visualizations that demonstrate how the model forecasts future stock prices based on historical data and market indicators.

#### 2 Key Components (Software Components)

- **Pandas:** Used for loading, cleaning, and manipulating stock market data.
- ➤ Matplotlib: Used for visualizing stock price trends, predictions, and model performance.
- ➤ Seaborn: Used for statistical plots like correlation heatmaps and data distributions.

**Scikit-learn**: Used for machine learning models, data splitting, and evaluation.

#### 3. Working

The process of building the AI-powered stock market predictor involves several key steps, including data exploration, visualization, and analysis. Below is a breakdown of how the project was executed, with a focus on the dataset of four companies: **AMZN**, **SPZ**, **BTC**, and **NFLX**.

#### 1. Data Loading and Initial Exploration

The first step was to load the stock data for the four companies using the Pandas library. The data was stored in a CSV file and loaded into a Pandas DataFrame using **pd.read\_csv()**. The dataset includes historical stock prices (e.g., opening and closing prices), trading volume, and date for each company. After loading the data, an initial inspection of the dataset was performed using methods like **data.head()** and **data.info()** to check the first few rows and understand the structure of the data, such as the number of records, column names, and missing values.

#### 2. Correlation Matrix

Next, we explored the relationships between the stock prices of the four companies by creating a **correlation matrix**. This matrix helps identify how the stock prices of different companies are related to each other. A high positive correlation (close to +1) indicates that the stock prices of two companies tend to move in the same direction, while a negative correlation (close to -1) suggests they move in opposite directions. Using **data.corr()**, we computed the correlation values between each company's stock price. Then, a **heatmap** was created using Seaborn (**sns.heatmap()**) to visualize the correlation matrix. The heatmap displayed the correlation values in a color-coded format, where darker colors indicated stronger correlations.

#### 3. Data Distribution and Visualizations

To understand the distribution of stock prices and their variations over time, we created several visualizations. These visualizations helped in understanding how each company's stock price behaves. Some of the key visualizations include:

 Histograms: We used sns.histplot() to plot the distribution of stock prices for each company. This showed the frequency of different stock price ranges and helped identify patterns such as whether the stock prices are skewed to higher or lower values.

- Bar Graphs: A bar plot was used to compare the average stock prices of the four companies. This provided a clear visual comparison of which company had the highest and lowest average stock prices over the given period.
- Distplots: To analyze the distribution of stock prices and better understand the probability density of the data, sns.distplot() was used. This plot shows the smooth curve of stock price distributions and helps in detecting any skewness or outliers in the data.

#### 4. Comparison of Companies

Using various plots, we performed comparisons between the stock prices of the four companies. We used **count plots** and **bar graphs** to compare certain aspects, like the total trading volume or the number of days the stock price crossed a specific threshold. This allowed us to visually inspect any significant trends or patterns, such as whether certain companies had higher volatility or more stable stock prices over time.

#### 5. Exploring Relationships

To gain deeper insights into the relationships between stock price movements and external factors, we compared the daily returns of each stock. The daily return is the percentage change in the stock price from one day to the next, which helps in understanding how volatile a particular stock is. to calculate daily returns for each stock and visualized the results using line plots and histograms to compare the return distributions of the four companies.

#### 6. Insights and Conclusion

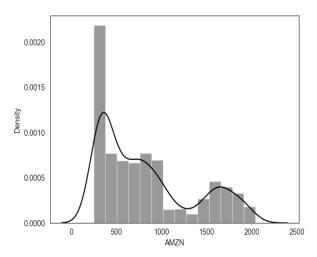
After performing the visual analysis and exploring the data, we observed key relationships between the stocks. For example, we may find that **AMZN** and **NFLX** have a high positive correlation, suggesting their prices tend to move in the same direction. On the other hand, **BTC** (Bitcoin) may show different behavior compared to traditional stocks like **AMZN** and **NFLX**, as cryptocurrencies are known to be more volatile.

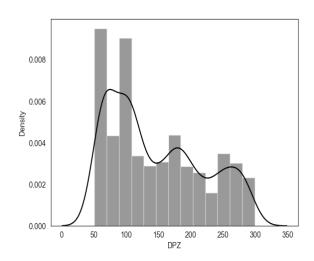
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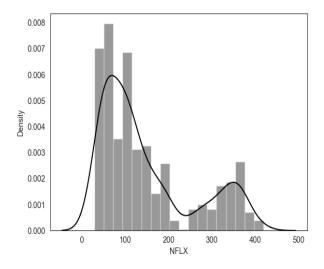
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

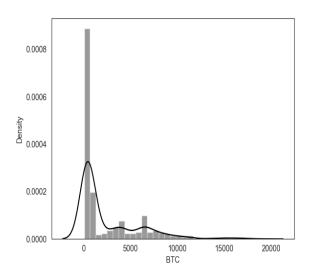
df=pd.read_csv("portfolio_data.csv")
print(df.info())
sb.set_style("white")

sb.distplot(df["AMZN"],kde=True,color="black")
plt.show()
```









```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

df = pd.read_csv("portfolio_data.csv")

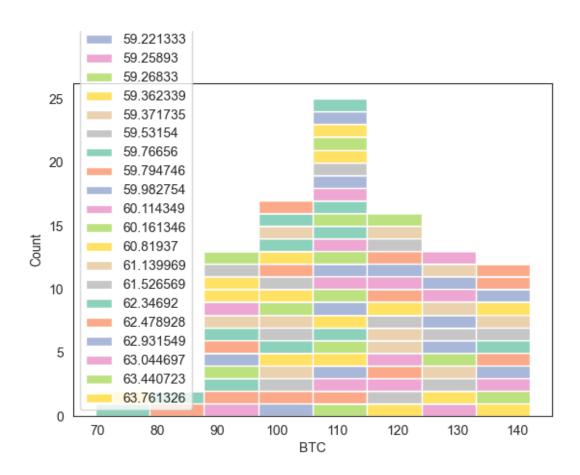
print(df.info())

df_melted = df[['DPZ', 'BTC', 'NFLX', 'AMZN']].melt(var_name='Stock', value_name='Value')

sb.set_style("white")

plt.figure(figsize=(10,6))
 sb.barplot(data=df_melted, x='Stock', y='Value', hue='Stock', palette="Set2")

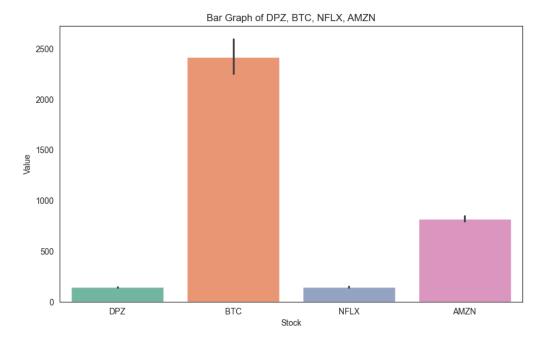
plt.title('Bar Graph of DPZ, BTC, NFLX, AMZN')
plt.show()
```



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

df=pd.read_csv("portfolio_data.csv")
print(df.head())
print(df.sample(10))
print(df.dtypes)
print(df.info())
print(df[["DPZ","BTC"]].mean())
```

```
======== RESTART: C:\Users\Shakthi\Desktop\duba\countour.py =========
      Date AMZN DPZ BTC NFLX
0 5/1/2013 248.229996 51.190983 106.250000 30.415714
  5/2/2013 252.550003 51.987320 98.099998
5/3/2013 258.049988 52.446388 112.900002
                                     98.099998 30.641428
                                                 30.492857
  5/6/2013 255.720001 53.205257 109.599998 30.098572
4 5/7/2013 257.730011 54.151505 113.199997 29.464285
            Date
                         AMZN
                                     DPZ
                                                     BTC
                                                                NFLX
                                           282.269989
                                                          46.501427
       1/6/2015
                  295.290009 90.292412
424
248
       4/25/2014
                   303.829987
                                69.972275
                                              457.869995
                                                           46.011429
                  757.250000 145.999237
                                            577.960022
      8/24/2016
                                                          95.180000
836
93
      9/12/2013
                  298.859985
                               61.526569
                                            140.660004
                                                           43.058571
619 10/14/2015
                  544.830017 100.825806
                                             254.440002 110.230003
1166 12/14/2017 1174.260010 180.481323 16467.910160 189.559998
1303 7/3/2018 1693.959961 278.234924 6590.060059 390.519989
791 6/21/2016 715.820007 124.082771 590.559998 90.989998
1167 12/15/2017 1179.140015 182.973145 17604.849610 190.119995
      1/4/2019 1575.390015 242.954697 3874.060059 297.570007
1430
Date
        object
AMZN
        float64
DPZ
        float64
       float64
BTC
       float64
dtype: object
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1520 entries, 0 to 1519
Data columns (total 5 columns):
# Column Non-Null Count Dtype
 0
    Date
           1520 non-null object
             1520 non-null
     AMZN
                            float64
     DPZ
             1520 non-null
   BTC
            1520 non-null float64
   NFLX
            1520 non-null
dtypes: float64(4), object(1)
memory usage: 59.5+ KB
None
DPZ
       146.771695
BTC
      2421.465669
dtype: float64
```



## 4. Advantages

- ❖ **Data Exploration**: Ensures the dataset is clean, correctly structured, and ready for analysis, preventing errors later on.
- ❖ Correlation Matrix: Helps identify relationships between stock prices, providing insights into how stocks move together. This is useful for portfolio diversification.
- ❖ Visualization: Visual tools like histograms and bar plots make it easy to spot trends, outliers, and patterns, aiding in better understanding of stock price behavior.
- ❖ Stock Comparison: Allows comparison of different stocks' performance, highlighting which are more volatile or stable, helping investors tailor strategies.
- ❖ Daily Returns Analysis: Helps assess stock volatility, essential for understanding risk and making informed investment decisions.

#### 5. Conclusion

This analysis of four companies—AMZN, SPZ, BTC, and NFLX—offers valuable insights into stock price behavior, volatility, and correlations. Using correlation matrices, visualizations, and daily returns analysis, we gained a deeper understanding of how these stocks behave over time. The findings provide a foundation for more advanced predictive models and can guide investment strategies. By understanding relationships between stocks and their volatility, investors can make better-informed decisions for portfolio management and risk assessment.