ವಿಶ್ವೇಶ್ವರಯ್ಯ ತಾಂತ್ರಿಕ ವಿಶ್ವವಿದ್ಯಾಲಯ, ಬೆಳಗಾವಿ
VISVESVARAYA TECHNOLOGICAL UNIVERSITY - BELAGAVI

Bangalore Institute of Technology

M.Tech, Department of Computer Science and Engineering

K R Road, V V Pura, Bengaluru-560004

Mini Project Report on

Tesla Stock Price Prediction

Submitted as Mini Project for the M.Tech Lab Component of IPCC subject

Artificial Intelligence and Machine Learning (22SCS22)

Submitted by

Spoorthy UK 1BI22SCS06

For academic year 2023-24

Under the guidance of

Dr. M S Bhargavi

Associate Professor

Dept. of CSE

ವಿಶ್ವೇಶ್ವರಯ್ಯ ತಾಂತ್ರಿಕ ವಿಶ್ವವಿದ್ಯಾಲಯ, ಬೆಳಗಾವಿ
VISVESVARAYA TECHNOLOGICAL UNIVERSITY - BELAGAVI

Bangalore Institute of Technology

M.Tech, Department of Computer Science and Engineering

K R Road, V V Pura, Bengaluru-560004

LABORATORY CERTIFICATE

This is to certify that Ms. Spoorthy UK bearing USN 1BI22SCS06 of II semester M.Tech, Computer Science & Engineering has satisfactorily completed the Mini Project for the M.Tech Lab Component of IPCC subject **Artificial Intelligence and Machine Learning (22SCS22)** prescribed by the Visvesvaraya Technological University for the year 2022 - 2023 .

10

Signature of the staff In-charge

CHAPTER 1

INTRODUCTION

1.1 Overview

The field of finance is a dynamic and ever-evolving domain where investors and analysts continuously seek to gain insights into the complex world of stock markets. One of the most intriguing and challenging endeavors within this realm is the prediction of stock price movements. Accurate stock price predictions can provide investors with a competitive edge, enabling them to make informed decisions and potentially maximize their returns. In this context, we delve into the exciting realm of stock price prediction, with a particular focus on one of the most prominent and innovative companies in the automotive industry: Tesla, Inc. Tesla has gained global recognition not only for its groundbreaking electric vehicles but also for its impact on financial markets. Its stock price has been subject to significant fluctuations, making it an ideal candidate for predictive analysis. The project centers on the application of advanced machine learning techniques to forecast the future movement of Tesla's stock prices. We will explore how historical stock price data, coupled with feature engineering and the power of machine learning models, can be harnessed to make predictions about whether Tesla's stock price will rise or fall. By doing so, we aim to provide a comprehensive understanding of the methodologies and tools used in stock price prediction, as well as the challenges and opportunities that this field presents.

Introduction

In today's ever-evolving financial landscape, the ability to predict stock price movements has become a paramount pursuit. Investors, analysts, and traders are increasingly turning to advanced technologies and machine learning to gain a competitive edge in the stock market. One of the captivating endeavors in this realm is the application of machine learning techniques to forecast the stock prices of prominent companies like Tesla Inc. (TSLA). Tesla, renowned for its innovations in electric vehicles and sustainable energy solutions, represents a captivating challenge in the world of stock market prediction. This project embarks on a journey to harness the power of data, algorithms, and predictive modeling to anticipate the future movements of Tesla's stock prices. In this pursuit, we delve into the realms of data analysis, feature engineering, model development, and evaluation, all with the aim of making more informed decisions in the dynamic world of financial markets.

1.2 Scope

The scope of the topic, which involves predicting stock prices using machine learning techniques with a focus on a specific company like Tesla, is extensive and holds significance in various domains. Here are some key aspects of the scope:

1. Financial Markets: Stock price prediction is of paramount importance in financial markets. Investors, traders, and financial institutions are constantly seeking accurate forecasts to make informed investment decisions, manage risks, and optimize their portfolios.

2.Investment Strategies: The topic can lead to the development of investment strategies, both for individual investors and institutional players. Predictive models can be used to identify potential buying or selling opportunities.

3. Risk Management: Accurate stock price predictions contribute to risk management. By understanding potential price movements, investors can take steps to protect their investments and mitigate losses.

4. Trading Algorithms: Machine learning models for stock price prediction are fundamental in the development of algorithmic trading strategies. These algorithms can execute trades based on real-time predictions, often within milliseconds.

5. Portfolio Management: Asset managers can use these predictive models to optimize and rebalance investment portfolios, aiming for higher returns while managing risks.

6. Investor Education: Understanding the methods used in stock price prediction can empower investors with knowledge to make better financial decisions.

7. Financial Research: Researchers and analysts can use these techniques to conduct studies on stock price behavior, market trends, and the impact of various factors on stock prices.

8. Broader Applications: While the primary focus is on stock price prediction, the techniques and methodologies learned in this context can be applied to other time series forecasting problems beyond the stock market.

9. Technological Advancements: As technology continues to evolve, the incorporation of artificial intelligence and machine learning in financial markets is expected to grow. This topic provides insights into cutting-edge technologies in finance.

10. Ethical and Regulatory Considerations: With the increasing use of automated trading systems, there are also ethical and regulatory considerations surrounding the use of predictive models in financial markets.

1.3 Applicability :

The applicability of a project focused on predicting stock prices using machine learning techniques, particularly in the context of a specific company like Tesla, extends to several domains and use cases. Here are some key areas where the project's findings and methodologies can be applied:

1.Investment Decision-Making: Individual investors, fund managers, and financial institutions can apply the predictive models developed in the project to make more informed investment decisions. These models can assist in selecting stocks, timing trades, and optimizing portfolios.

2 Algorithmic Trading: The project's machine learning models can serve as the foundation for algorithmic trading strategies. Algorithmic traders can use these models to automate the execution of buy and sell orders based on real-time predictions, potentially gaining an edge in high-frequency trading.

3 Risk Management: Investors can use the project's predictive models to manage and mitigate risks associated with their investments. By understanding potential price movements, they can implement risk management strategies and stop-loss orders.

4 Portfolio Optimization: Asset managers and wealth advisors can leverage the project's methodologies to optimize client portfolios. These models can help in asset allocation decisions, considering risk-adjusted returns.

5 Financial Research: Researchers and analysts in the finance industry can apply the project's techniques to conduct empirical studies on stock price behavior, market anomalies, and the impact of various factors on stock prices. This research can contribute to financial literature.

6 Education and Training: The project can be used as an educational resource for individuals interested in finance and machine learning. It can serve as a practical example of applying data science techniques to real-world financial data.

7 Market Sentiment Analysis: Sentiment analysis and news sentiment data can be incorporated into the predictive models to gauge market sentiment and its potential impact on stock prices.

8 Trading Strategies Development: Traders and quant developers can extend the project by developing more advanced trading strategies, including pairs trading, mean-reversion, and statistical arbitrage strategies, using the predictive models as a foundation.

9 Financial Technology (FinTech): FinTech companies can integrate the project's predictive models into their platforms to provide retail investors with AI-driven insights and trading recommendations.

10 Regulatory Compliance: Financial regulators and compliance departments in financial institutions can use predictive models to monitor trading activities and detect potential market manipulation or insider trading.

CHAPTER 2

PROBLEM STATEMENT

2.1 Problem Statement

Develop accurate machine learning models to predict Tesla Inc. (TSLA) stock's future closing prices. The challenge involves accounting for market volatility, non-stationary data, and various factors influencing stock price movements. The objective is to empower stakeholders with reliable tools for making informed decisions regarding TSLA stock, optimizing portfolios, and managing risk in a dynamic financial environment.

Objective

- The primary objective of this project is to create machine learning models capable of accurately forecasting Tesla Inc. (TSLA) stock's future closing prices.
- The project aims to provide practical value to investors and financial analysts by offering reliable predictive tools for decision-making in the stock market.

2.2 Dataset description with Snapshot of dataset

The dataset used in this project contains historical data of Tesla (TSLA) stock. It includes various features related to the stock's performance over time. Here is an updated description of the columns present in the dataset:

1. **Date:** The date column is essential for tracking the chronological order of stock price data.

2.Open: The opening price is the first traded price of the stock on a given day. It can be an important indicator of market sentiment at the start of a trading session.

3.High: The highest price reached by Tesla stock during the day. These prices represent the highest and lowest prices reached during the trading day. They provide insights into price volatility.

4.Low: The lowest price reached by Tesla stock during the day. These prices represent the highest and lowest prices reached during the trading day. They provide insights into price volatility.

5.Close: The closing price is the last traded price of the stock on a given day. It is a crucial reference point for assessing the overall performance of the stock during the trading session.

6.Adj Close: TThe adjusted closing price accounts for corporate actions that can affect stock prices. It is often used for calculating returns and assessing the stock's true performance.

7. **Volume:** The volume represents the total number of shares traded on a specific day. It is a key indicator of market activity and liquidity.

1	Date	Open	High	Low	Close	Adj Close	Volume
2	29-06-2010	19	25	17.540001	23.889999	23.889999	18766300
3	30-06-2010	25.790001	30.42	23.299999	23.83	23.83	17187100
4	01-07-2010	25	25.92	20.27	21.959999	21.959999	8218800
5	02-07-2010	23	23.1	18.709999	19.200001	19.200001	5139800
6	06-07-2010	20	20	15.83	16.110001	16.110001	6866900
7	07-07-2010	16.4	16.629999	14.98	15.8	15.8	6921700
8	08-07-2010	16.139999	17.52	15.57	17.459999	17.459999	7711400
9	09-07-2010	17.58	17.9	16.549999	17.4	17.4	4050600
10	12-07-2010	17.950001	18.07	17	17.049999	17.049999	2202500
11	13-07-2010	17.389999	18.639999	16.9	18.139999	18.139999	2680100
12	14-07-2010	17.940001	20.15	17.76	19.84	19.84	4195200
13	15-07-2010	19.940001	21.5	19	19.889999	19.889999	3739800
14	16-07-2010	20.700001	21.299999	20.049999	20.639999	20.639999	2621300
15	19-07-2010	21.370001	22.25	20.92	21.91	21.91	2486500
16	20-07-2010	21.85	21.85	20.049999	20.299999	20.299999	1825300
17	21-07-2010	20.66	20.9	19.5	20.219999	20.219999	1252500
18	22-07-2010	20.5	21.25	20.370001	21	21	957800
19	23-07-2010	21.190001	21.559999	21.059999	21.290001	21.290001	653600
20	26-07-2010	21.5	21.5	20.299999	20.950001	20.950001	922200

Figure 1: Snapshot-1

21	27-07-2010	20.91	21.18	20.26	20.549999	20.549999	619700
22	28-07-2010	20.549999	20.9	20.51	20.719999	20.719999	467200
23	29-07-2010	20.77	20.879999	20	20.35	20.35	616000
24	30-07-2010	20.200001	20.440001	19.549999	19.940001	19.940001	426900
25	02-08-2010	20.5	20.969999	20.33	20.92	20.92	718100
26	03-08-2010	21	21.950001	20.82	21.950001	21.950001	1230500
27	04-08-2010	21.950001	22.18	20.85	21.26	21.26	913000
28	05-08-2010	21.540001	21.549999	20.049999	20.450001	20.450001	796200
29	06-08-2010	20.1	20.16	19.52	19.59	19.59	741900
30	09-08-2010	19.9	19.98	19.450001	19.6	19.6	812700
31	10-08-2010	19.65	19.65	18.82	19.030001	19.030001	1281300
32	11-08-2010	18.690001	18.879999	17.85	17.9	17.9	797600
33	12-08-2010	17.799999	17.9	17.389999	17.6	17.6	691000
34	13-08-2010	18.18	18.450001	17.66	18.32	18.32	634000
35	16-08-2010	18.450001	18.799999	18.26	18.780001	18.780001	485800
36	17-08-2010	18.959999	19.4	18.780001	19.15	19.15	447900
37	18-08-2010	19.59	19.59	18.6	18.77	18.77	601300
38	19-08-2010	18.540001	19.25	18.33	18.790001	18.790001	579100
39	20-08-2010	18.65	19.110001	18.51	19.1	19.1	296000

Figure 2: Snapshot-2

2.3 List of all Objectives

- **Accurate Stock Price Prediction:** Develop machine learning models capable of accurately forecasting TSLA's daily closing prices over a specified time horizon.

- **Risk Assessment:** Provide investors and analysts with a means to assess the risk associated with TSLA stock investments by offering reliable price predictions.

- **Decision Support:** Offer decision support tools to assist investors, traders, and financial analysts in making informed choices regarding TSLA stock, including buy/sell decisions and portfolio optimization.

- **Insight Generation:** Generate actionable insights into TSLA's stock price behavior, including identifying potential trends, patterns, and factors influencing price movements.

- **Performance Comparison:** Compare the performance of different machine learning algorithms, such as Logistic Regression, Support Vector Machines (SVM), and Random Forest, to determine which model yields the most accurate predictions.

- **Evaluation Metrics:** Employ appropriate evaluation metrics, such as accuracy, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Receiver Operating Characteristic Area Under the Curve (ROC AUC), to quantitatively assess the models' performance.

- **Visualization:** Visualize the predicted vs. actual stock prices through graphs and charts, enhancing the interpretability of model outcomes.

- **Use Case Applications: I**dentify and explore practical applications of the predictive models, including their use in trading strategies, risk management, and portfolio optimization

CHAPTER 3

SYSTEM REQUIREMENT SPECIFICATION

3.1 Requirement Definition

In the context of this project, "requirements" refer to the detailed descriptions and specifications of what the Tesla Stock Prediction should accomplish and how it should function. These requirements serve as a comprehensive guide that outlines the functionalities, features, constraints, and expectations for the system's development. The "Requirements Specification" section of project outlines the specific functionalities and criteria that the proposed system should fulfill. The detailed breakdown of the requirements specification for Tesla stock prediction project using ensemble techniques and machine learning algorithms:

3.1.1 Requirements Specification

Requirement definition for a project involving machine learning-based stock price prediction for Tesla Inc. (TSLA) includes specifying the functional and non-functional requirements. Here's a breakdown of these requirements:

3.1.2 Functional Requirements

Data Collection and Preprocessing

The system should be able to collect historical TSLA stock price data from a reliable source, such as financial databases or APIs.

Feature Engineering:

The system should perform feature engineering to create relevant features, such as technical indicators or sentiment scores, to improve prediction accuracy.

Model Training:

The system should train machine learning models using historical stock price data and relevant features.

Hyperparameter Tuning:

The system should implement hyperparameter tuning techniques to optimize model performance.

Evaluation and Validation:

It should provide tools for evaluating model performance using appropriate metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Visualization:

The system should enable users to visualize stock price predictions, actual prices, and evaluation metrics through charts and graphs.Non-Functional Requirements

Non-Functional Requirements:

Performance:

The system should be capable of handling large datasets efficiently. Model training and prediction should be completed within a reasonable time frame.

Accuracy:

The models should aim for a high level of prediction accuracy to assist investors and analysts effectively.

Security:

Data privacy and security measures should be in place to protect sensitive financial data.

Usability:

The system's user interface should be intuitive, making it accessible to both technical and non-technical users.

Scalability:

The system should be designed to accommodate future updates and enhancements, including the incorporation of additional data sources or features.

Reliability:

The system should be reliable, with minimal downtime and robust error handling.

Compatibility:

It should be compatible with a variety of operating systems and browsers.

3.2 Hardware Requirements

Table 3.2: Hardware Requirements

Hardware Component	Description
Computer with Adequate RAM	A computer with at least 8GB of RAM
CPU	A modern multi-core processor (e.g., Intel Core i5)
Storage	You should have sufficient storage space (e.g., 256GB SSD) to store datasets
Internet Connectivity	A stable and reasonably fast internet connection is necessary for data downloading

3.3 Software Requirements

Table 3.3: Software Requirements

Requirement	Description
Operating System	Windows, Linux, macOS
Programming Languages	Python
Development Environment	IDE : Visual Studio Code
Libraries and Frameworks	Python (with libraries like scikit-learn, pandas, numpy)
Data Visualization Tools	Matplotlib and Seaborn (for data visualization)
Data Mining Libraries	Scikit-learn (for machine learning and data mining)

3.4 Summary

This requirement specification serves as a foundation for the development of the "Tesla Stock Price Prediction" system. It outlines the software and hardware requirements, as well as the functional and non-functional requirements necessary to create a robust and effective solution.

CHAPTER 4

SYSTEM DESIGN

4.1 System Design

The system design outlines the architecture and components of Tesla Stock Price Prediction project. It encompasses the data flow, algorithms integration, and user interaction. The design ensures that the project's functional and non-functional requirements are met effectively.

4.2 Flow Chart

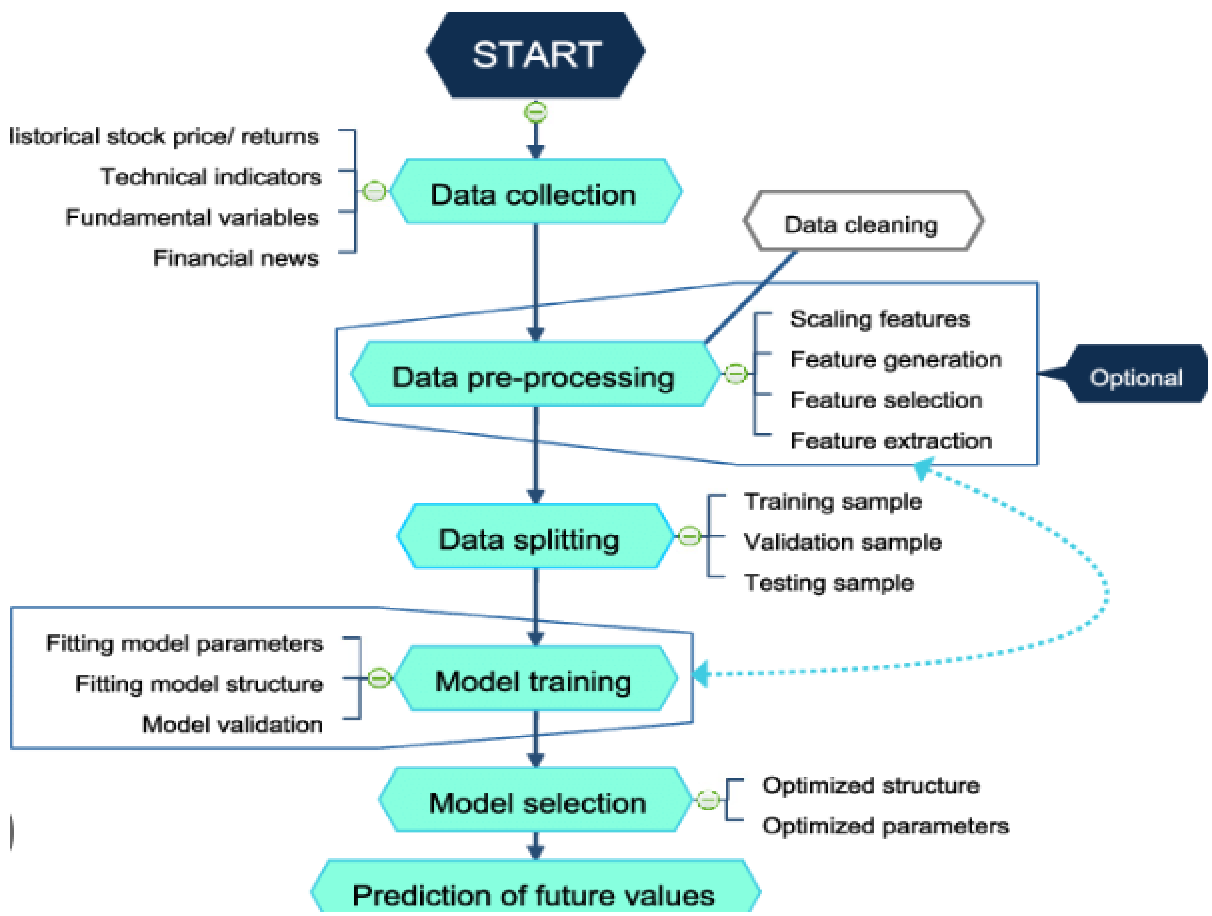


Fig 3: Snapshot

4.3 System Architecture

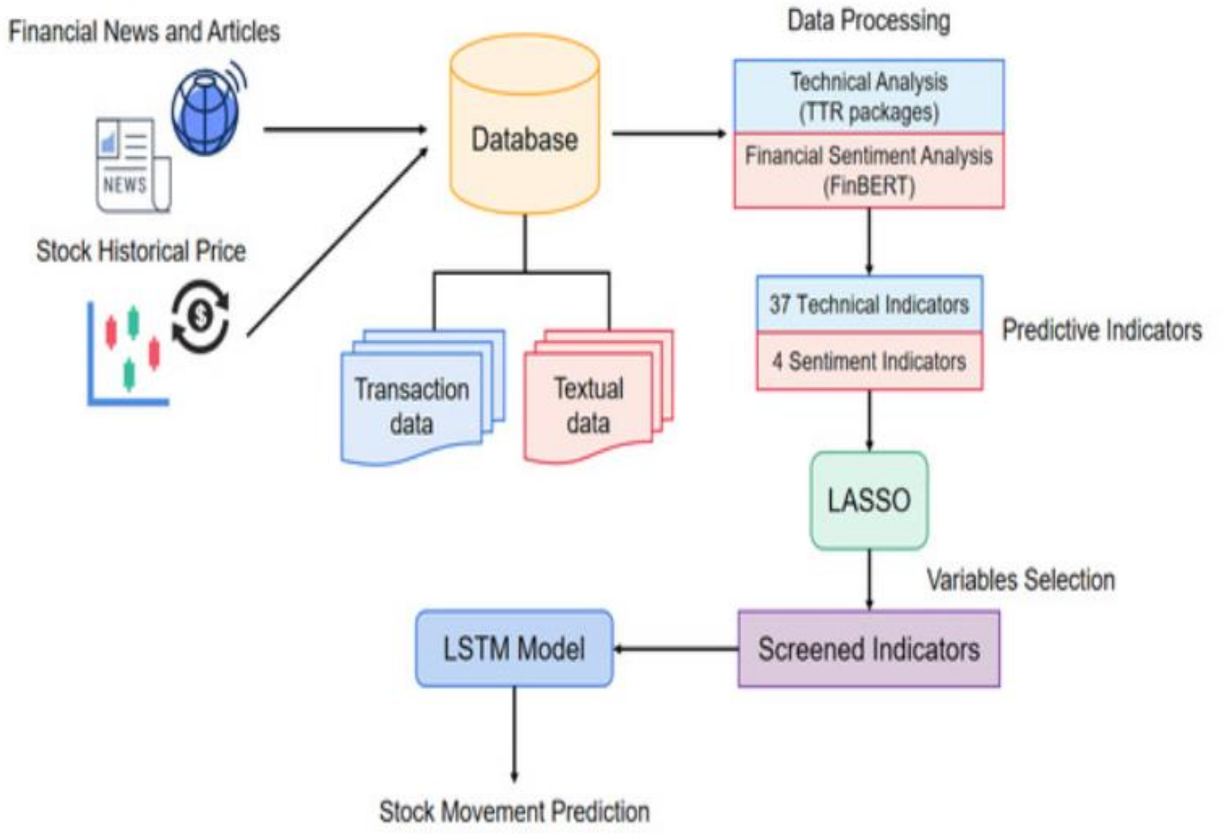


Figure 4: System Architecture

ML techniques that could be applied in predicting Tesla Stock price are:

1. Time Series Analysis: Since stock price data is typically sequential and exhibits temporal dependencies, time series analysis techniques can be employed. These include methods such as autoregressive integrated moving average (ARIMA), seasonal decomposition of time series (STL), and exponential smoothing models.

2. Machine Learning Algorithms: Various machine learning algorithms can be applied to stock price prediction. These include regression algorithms like Linear Regression and Ridge Regression, ensemble methods like Random Forest and Gradient Boosting, and neural network models like Long Short-Term Memory (LSTM) or Convolutional Neural Networks (CNNs).

3. Feature Engineering: Creating informative and relevant features from the available data can improve prediction accuracy. Feature engineering techniques involve transforming or combining existing features to extract meaningful information. For example, creating lagged variables (using past price or volume data), technical indicators (moving averages, relative strength index), or sentiment analysis of news and social media data.

4. Technical Analysis Indicators: Technical analysis techniques can be used to extract patterns and trends from historical price data. These include indicators such as moving averages, Bollinger Bands, relative strength index (RSI), and MACD (Moving Average Convergence Divergence). Incorporating these indicators as features can enhance the predictive power of the modelsTools to be used Python

Python is a widely used programming language for machine learning and data analysis. It offers a rich ecosystem of libraries and frameworks for implementing prediction models. Some popular Python libraries include:

a. **Scikit-learn:** Scikit-learn is a comprehensive machine learning library that provides various algorithms for classification, regression, and model evaluation.
b. **Pandas:** Pandas is a data manipulation library that provides powerful tools for data preprocessing, cleaning, and feature engineering.
c. **NumPy:** NumPy is a fundamental library for scientific computing in Python, providing support for numerical operations and array manipulations. **Matplotlib:** A plotting library used to create various types of visualizations,such as line plots, scatter plots, and histograms.
d. **Seaborn:** A statistical data visualization library that builds on top of Matplotlib, providing enhanced visualizations and statistical plotting function.
e. **SciPy:** A library that provides functions for scientific and technical computing, including statistical operations and optimization algorithms.

IDE Used: Visual Studio Code.

4.4 Methodology:

1.Data preprocessing: This involves handling missing values, dropping irrelevant columns, and normalizing or scaling the data as necessary.

2.Feature engineering: Creating additional features based on domain knowledge or patterns observed in the data that could potentially improve the model's performance.

3.Splitting the data: Dividing the dataset into training and testing sets, ensuring that the model's performance is evaluated on unseen data.

4.Model selection and training: Experimenting with different machine learning algorithms such as Logistic Regression, Support Vector Classifier (SVC). Training the models using the training data and optimizing their hyperparameters if necessary.

5.Model evaluation: Assessing the performance of the trained models using appropriate evaluation metrics such as ROC AUC score. Comparing the results to determine the bestperforming model.

6.Prediction and analysis: Utilizing the selected model to make predictions on new, unseen data. Analyzing the results and evaluating the model's reliability and usefulness in predicting Tesla stock price movements

CHAPTER 5

IMPLEMENTION

5.1 Implementation

Implementing a Tesla Stock Price Prediction project involves several key steps and considerations:

1. **Data Collection:** Gather historical stock price data for the target company, such as Tesla (TSLA), from reliable sources. Common sources include financial APIs, web scraping, or downloadable datasets.
2. **Data Preprocessing:** Clean and preprocess the collected data. This includes handling missing values, formatting dates, and performing feature engineering. Feature engineering may involve creating new features from existing ones, such as moving averages or technical indicators.
3. **Exploratory Data Analysis (EDA):** Conduct EDA to gain insights into the data. Visualize the data using tools like Matplotlib and Seaborn to understand trends, correlations, and potential outliers.
4. **Feature Selection:** Select relevant features for the prediction task. Use techniques like correlation analysis or feature importance from machine learning models to determine the most impactful features.
5. **Model Selection:** Choose appropriate machine learning algorithms for the prediction task. Common models include linear regression, support vector machines (SVM), and ensemble methods like random forests.
6. **Model Training:** Split the dataset into training and testing sets. Train the selected models on the training data. Ensure proper hyperparameter tuning and optimization.
7. **Model Evaluation:** Evaluate model performance using appropriate metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or R-squared (R2) for regression tasks. For classification tasks, use metrics like accuracy, precision, recall, and ROC AUC.

5.2 Source code

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve

import warnings
warnings.filterwarnings('ignore')



# Load the dataset
df = pd.read_csv("C:/Users/ukshr/OneDrive/Desktop/tesla/TSLA.csv")

df = df.drop(['Adj Close'], axis=1)

# Feature engineering
df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y')
df['day'] = df['Date'].dt.day
df['month'] = df['Date'].dt.month
df['year'] = df['Date'].dt.year
df['is_quarter_end'] = np.where(df['Date'].dt.is_quarter_end, 1, 0)

# Create the 'target' column
```

```
df['target'] = np.where(df['Close'].shift(-1) > df['Close'], 1, 0)

# Visualizations
plt.figure(figsize=(15, 5))
plt.plot(df['Close'])
plt.title('Tesla Close Price', fontsize=15)
plt.ylabel('Price in Dollars')
plt.show()

features = ['Open', 'High', 'Low', 'Close', 'Volume']
plt.figure(figsize=(20, 10))
for i, col in enumerate(features):
    plt.subplot(2, 3, i + 1)
    sb.distplot(df[col], bins=20, kde=True)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()

plt.figure(figsize=(20, 10))
for i, col in enumerate(features):
    plt.subplot(2, 3, i + 1)
    sb.boxplot(data=df, y=col)
    plt.title(f'Box Plot of {col}')
plt.tight_layout()
plt.show()

# Correlation heatmap
plt.figure(figsize=(10, 10))
sb.heatmap(df.corr() > 0.9, annot=True, cbar=False)
plt.title('Correlation Matrix')
plt.show()
```

```
# Prepare features and target
features = df[['Open', 'Close', 'Volume', 'day', 'month', 'year', 'is_quarter_end']]
target = df['target']

scaler = StandardScaler()
features = scaler.fit_transform(features)

X_train, X_valid, Y_train, Y_valid = train_test_split(
    features, target, test_size=0.1, random_state=2022)

# Model training and evaluation
models = [LogisticRegression(), SVC(kernel='poly', probability=True),
RandomForestClassifier()]

for model in models:
    model.fit(X_train, Y_train)
    print(f'{model} : ')
    print('Training AUC : ', roc_auc_score(Y_train, model.predict_proba(X_train)[:, 1]))
    print('Validation AUC : ', roc_auc_score(Y_valid, model.predict_proba(X_valid)[:, 1]))
    print()

    # Confusion matrix
    plt.figure(figsize=(8, 6))
    cm = confusion_matrix(Y_valid, model.predict(X_valid))
    sb.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.title(f'Confusion Matrix - {model}')
    plt.show()
    # AUC graph
    plt.figure(figsize=(10, 6))
```

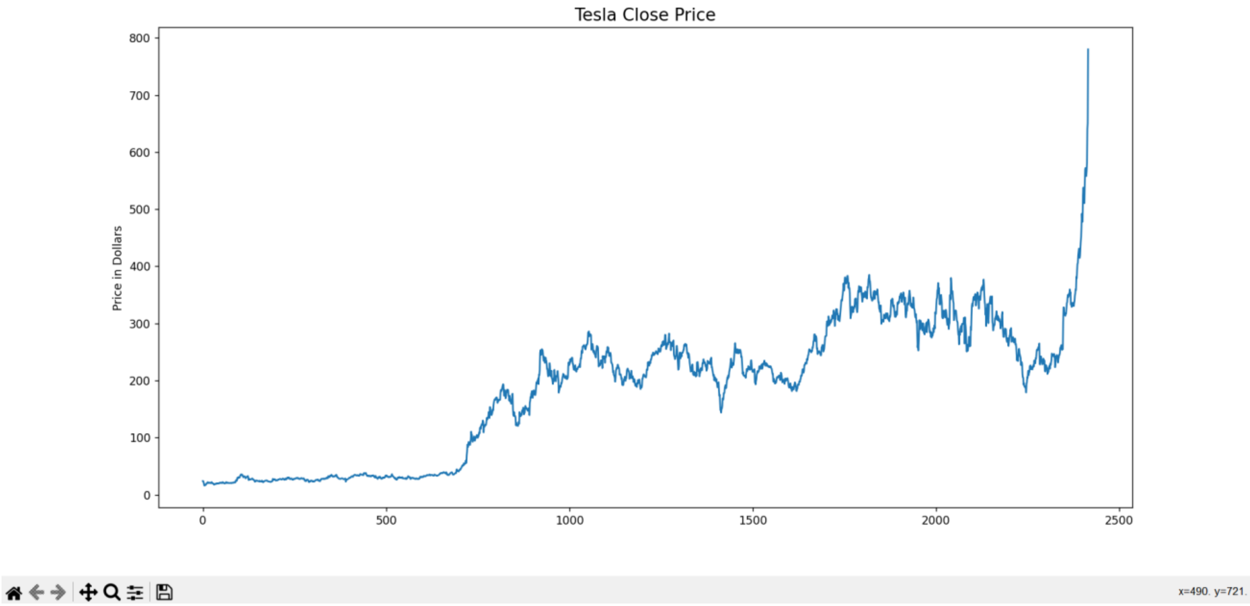
```
Y_pred_proba = model.predict_proba(X_valid)[:, 1]
fpr, tpr, _ = roc_curve(Y_valid, Y_pred_proba)
auc = roc_auc_score(Y_valid, Y_pred_proba)
plt.plot(fpr, tpr, label=f'{model} (AUC = {auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(f'ROC Curve - {model}')
plt.legend(loc="lower right")
plt.show()
```

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve

import warnings
warnings.filterwarnings('ignore')
```

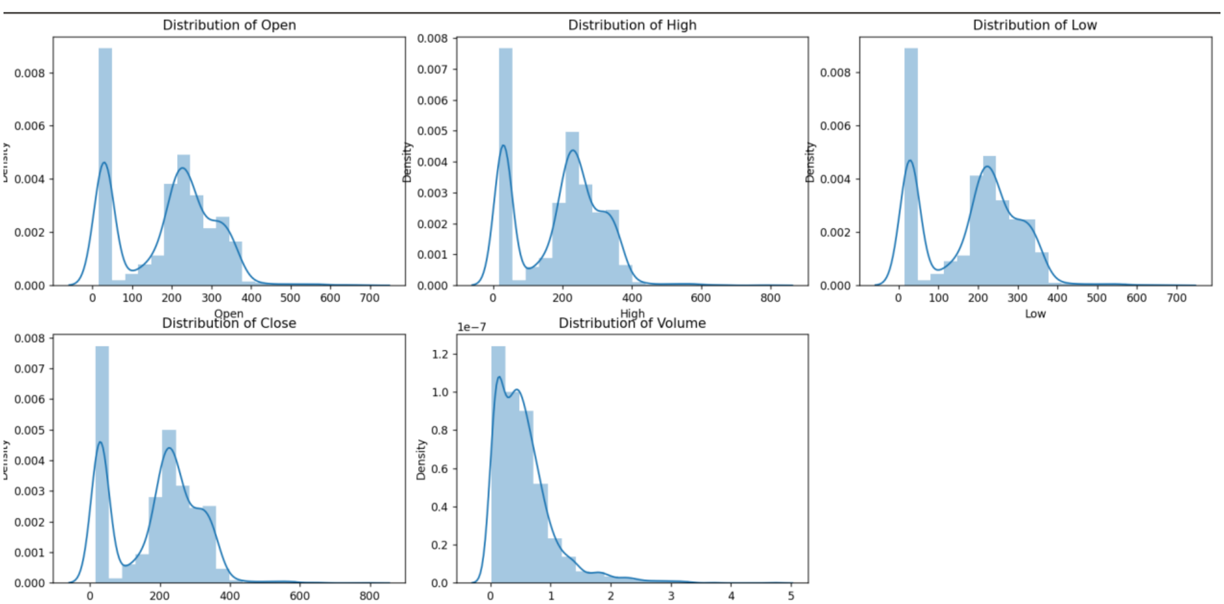
CHAPTER 6

RESULTS

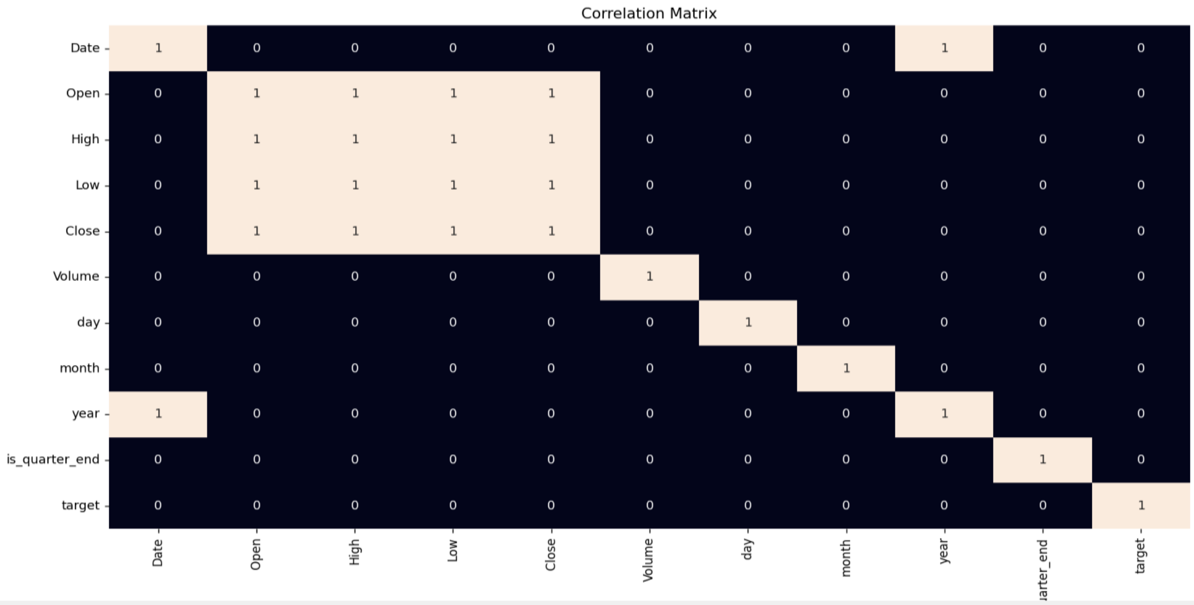
Results



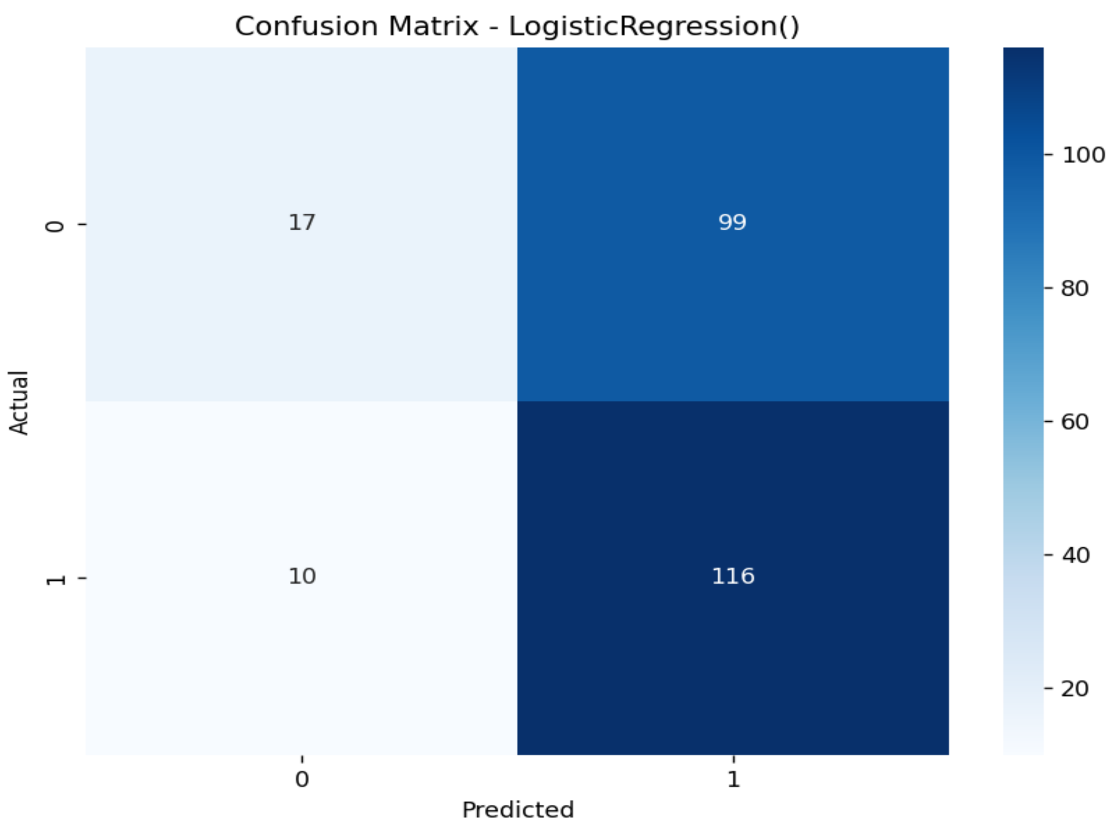
Snapshot-1



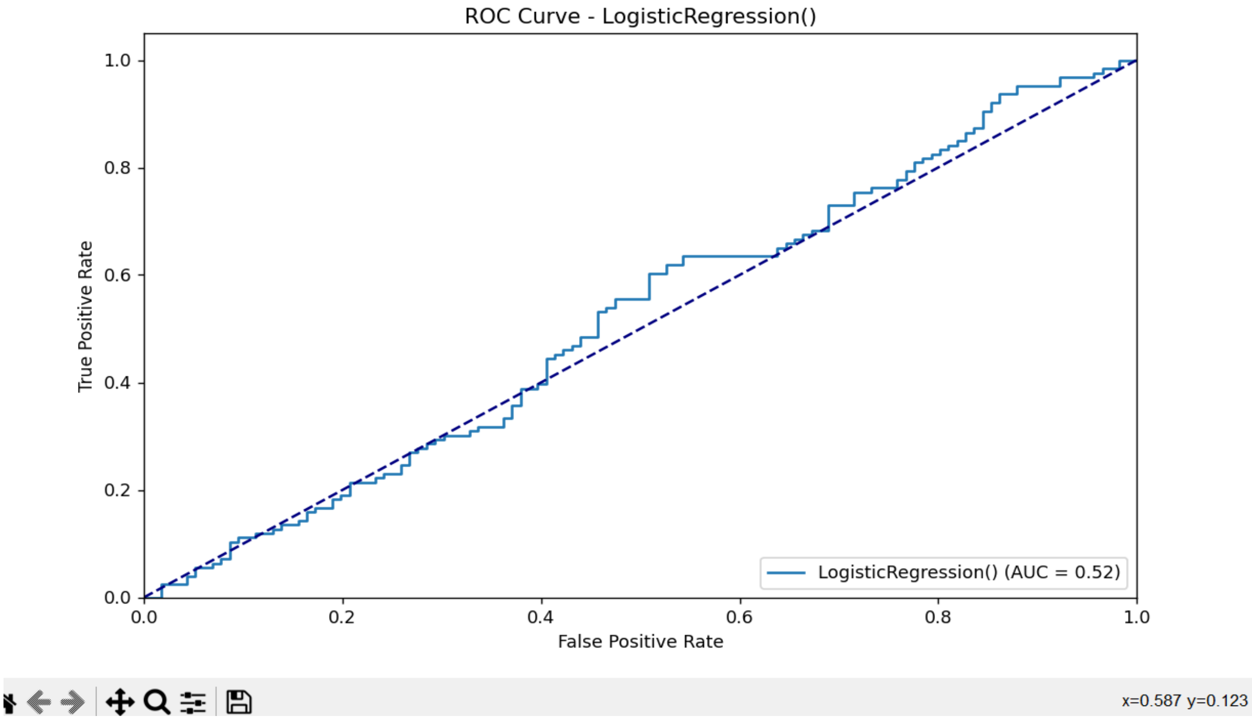
Snapshot-2



Snapshot-3



Snapshot-4



Snapshot-5

```
LogisticRegression() :
Training AUC :  0.5195477040179157
Validation AUC :  0.5184044882320744

SVC(kernel='poly', probability=True) :
Training AUC :  0.5631072276762469
Validation AUC :  0.49148193760262726

RandomForestClassifier() :
Training AUC :  1.0
Validation AUC :  0.4821770662287904
```

Snapshot-6

CHAPTER 7

CONCLUSION

Conclusion and Future Work

The "Tesla Stock Price Prediction using Machine Learning" project concludes with valuable insights into the world of stock market prediction and the practical application of data science and machine learning techniques. Through rigorous analysis, model development, and evaluation, the project sheds light on the possibilities and challenges of forecasting stock price movements.

Future Work

In future work, the stock price prediction project can be extended in several ways. Firstly, more advanced machine learning techniques, such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, can be explored to capture complex temporal dependencies in stock price data. Additionally, the project can benefit from incorporating external data sources, such as news sentiment analysis or macroeconomic indicators, to enhance prediction accuracy. Implementing a real-time prediction system for live trading and refining trading strategies through reinforcement learning methods presents another avenue for future development. Lastly, the project can be adapted for predicting stock prices of multiple companies, transforming it into a versatile tool for investors and financial analysts.

REFERENCE

[1].Agrawal M, Shukla PK, Nair R, Nayyar A, Masud M. 2022. Stock prediction based on technical indicators using deep learning model. Computers, Materials & Continua 70(1):287-304

[2] Baker M, Stein JC. 2004. Market liquidity as a sentiment indicator. Journal of Financial Markets 7(3):271-299

[3] Borges MR. 2010. Efficient market hypothesis in European stock markets. The European Journal of Finance 16(7):711-726

[4] Boyacioglu MA, Avci D. 2010. An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange. Expert Systems with Applications 37(12):7908-7912

[5] Breheny P, Huang J. 2011. Coordinate descent algorithms for nonconvex penalized regression, with applications to biological feature selection. The Annals of Applied Statistics 5(1):232-253