

STOCK PREDICTION SYSTEM

MINI PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

This project aims to develop a robust predictive model for stock market forecasting using historical price and trading volume data. The dataset comprises columns such as detailing daily stock transactions across multiple companies, with attributes such as opening and closing prices, daily highs and lows, trading volumes, and trading dates. These features provide a comprehensive view of market activities, adjusted for stock splits, making the data highly suitable for time series analysis and forecasting. The primary objective of the project is to analyze historical trends and patterns in the data to predict future stock prices. Leveraging advanced machine learning techniques, such as regression models, neural networks, and time series models like ARIMA or LSTMs, the project will explore relationships between price movements, trading volumes, and temporal patterns. This analysis will have significant real world applications, particularly in investment strategy formulation, risk assessment, and financial decision making. By offering insights into potential future price movements, the project aims to empower investors with data driven tools for optimizing their portfolio performance

Keywords:

Predictive Maintenance, Machine Learning Algorithms, Imbalanced Dataset Handling, Data Preprocessing, Hyperparameter Tuning

Dataset Link:

[https://www.kaggle.com/code/l33tc0d3r/stock price prediction/input?select=prices split adjusted.csv](https://www.kaggle.com/code/l33tc0d3r/stock-price-prediction/input?select=prices%20split%20adjusted.csv)

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF THE PROBLEM STATEMENT:

The primary goal of this project is to create a predictive model for stock market forecasting by analyzing historical data. Stock market data includes various attributes such as opening and closing prices, daily highs and lows, and trading volumes, all of which are influenced by economic indicators, market sentiment, and global events. The time series nature of stock prices requires specialized models that can handle temporal dependencies and autocorrelation, beyond traditional regression models. Financial markets are inherently noisy and volatile, making it challenging to filter out noise and capture meaningful patterns. Effective feature engineering is crucial, involving the creation of technical indicators, lagged variables, and other derived features. Model selection and evaluation are essential, comparing algorithms like ARIMA, LSTM, and regression based approaches. The project's ultimate goal is to provide actionable insights for investors, helping with investment strategy formulation, risk assessment, and financial decision making, by leveraging advanced machine learning techniques.

1.2 OBJECTIVES:

The primary objective of this project is to create a predictive model for stock market forecasting using historical price and trading volume data. By employing advanced machine learning techniques and time series models like ARIMA and LSTM, the project aims to enhance predictive accuracy. Key tasks include effective feature engineering, noise reduction, and rigorous model evaluation to capture meaningful patterns. The ultimate goal is to provide actionable insights for investors, aiding in investment strategy formulation, risk assessment, and financial decision making. This project seeks to deliver a practical and reliable tool for optimizing portfolio performance.

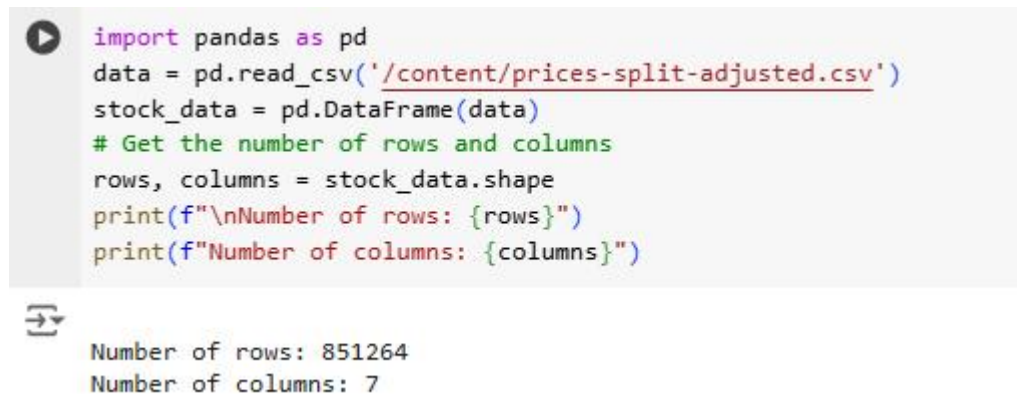
CHAPTER 2

DATASET DESCRIPTION

2.1 DATASET COLLECTION:

The dataset for this project was collected from historical stock market records, providing daily transaction details for various companies. It includes essential attributes such as trading date, stock ticker symbol, opening and closing prices, daily highs and lows, and trading volumes. The dataset spans multiple years and is adjusted for stock splits, ensuring consistency and reliability for analysis. These features enable comprehensive insights into market activities, making the dataset well suited for time series forecasting. Stored in CSV format, the data forms the basis for developing advanced machine learning models to predict stock prices and support investment decision making.

2.2 DATASET SIZE AND STRUCTURE :



```
import pandas as pd
data = pd.read_csv('/content/prices-split-adjusted.csv')
stock_data = pd.DataFrame(data)
# Get the number of rows and columns
rows, columns = stock_data.shape
print(f"\nNumber of rows: {rows}")
print(f"Number of columns: {columns}")
```

Number of rows: 851264
Number of columns: 7

Fig 2.1 Dataset Description

851264 rows and 7 columns (after combining train and test sets).

The **PRICES SPLIT ADJUSTED Dataset** consists of:

- 1 **Date:** The trading date for each stock.
- 2 **Symbol:** The stock ticker symbol, representing individual companies.
- 3 **Open:** The stock's opening price for the trading day.
- 4 **Close:** The stock's closing price for the trading day.
- 5 **Low:** The lowest price recorded during the trading day.
- 6 **High:** The highest price recorded during the trading day.
- 7 **Volume:** The total number of shares traded during the day.

2.3 DATASET FEATURES DESCRIPTION

- i. **Date:** The specific trading date, providing the temporal dimension for tracking stock market activities.
- ii. **Symbol:** A unique ticker symbol representing each company, used to differentiate stocks in the dataset.
- iii. **Open:** The opening price of the stock for the trading day, indicating initial market sentiment.
- iv. **Close:** The closing price of the stock for the trading day, often used for trend and performance analysis.
- v. **Low:** The lowest price recorded during the trading day, reflecting the minimum valuation of the stock.
- vi. **High:** The highest price recorded during the trading day, showing peak market valuation.
- vii. **Volume:** The total number of shares traded during the day, providing insights into market activity and liquidity.

CHAPTER 3

DATA ACQUISITION AND INITIAL ANALYSIS

3.1 DATA LOADING:

The dataset, provided in CSV format as `prices split adjusted.csv`, was loaded into a structured dataframe using Python's pandas library, which is well suited for handling tabular data. This step ensured the dataset was readily accessible for further processing and analysis. The file contains key columns such as date, symbol, open, close, low, high, and volume, each essential for analyzing stock market trends. After loading, the data underwent initial validation to confirm the correct interpretation of all attributes. Missing values, duplicate records, and inconsistent entries were identified as part of the quality check to ensure the data's reliability. Additionally, the data types of each column were reviewed to ensure compatibility with the analytical processes. These preliminary steps were critical to preparing the dataset for effective exploration, preprocessing, and model development, ensuring that the data was clean, structured, and ready for use in predictive modeling tasks.

3.2 INITIAL OBSERVATIONS:

Upon initial examination of the dataset, several key features were identified that are crucial for stock market analysis. The dataset includes columns such as the date, stock symbol, open price, close price, high, low, and trading volume. These features provide valuable insights into daily market behavior and form the basis for time series analysis. The dataset spans multiple companies, with each stock represented by a unique ticker symbol, allowing for cross sectional analysis across various market sectors. The date column ensures a temporal structure, essential for modeling stock price trends over time. Initial checks showed no significant data integrity issues, such as missing or incorrectly formatted values, although further exploration for outliers and anomalies is necessary. The high consistency and quality of the data at this stage indicate that the dataset is well suited for the next steps, including feature engineering, trend analysis, and the development of predictive models. These initial observations have helped outline the preprocessing steps and confirmed the dataset's potential for developing a robust predictive model for stock forecasting.

CHAPTER 4

DATA CLEANING AND PREPROCESSING

Data cleaning and preprocessing are crucial steps to ensure the quality and reliability of the dataset for analysis. In this project, the dataset was checked for missing values, duplicates, and inconsistencies. Any missing or incorrect entries were either removed or imputed based on the context. The data types of each column were verified to ensure compatibility with the intended analysis, such as converting the date column into a datetime format. Additionally, outlier detection was performed to identify any extreme values that could skew the results. This process laid the foundation for effective feature engineering and model development.

4.1 HANDLING MISSING VALUES:

```
print("### Missing Values Before Cleaning ###")
print(df.isnull().sum())

# Remove rows with null values
df_cleaned = df.dropna()

# Verify if all null values are removed
print("\n### Missing Values After Cleaning ###")
print(df_cleaned.isnull().sum())

# Display the new shape of the dataset
print("\nOriginal Dataset Shape:", df.shape)
print("Cleaned Dataset Shape:", df_cleaned.shape)
```



```
### Missing Values Before Cleaning ###
date      0
symbol    0
open      0
close     0
low       0
high      0
volume    0
dtype: int64

### Missing Values After Cleaning ###
date      0
symbol    0
open      0
close     0
low       0
high      0
volume    0
dtype: int64

Original Dataset Shape: (851264, 7)
Cleaned Dataset Shape: (851264, 7)
```

Fig 4.1 Handling missing values

Missing values in the stock market dataset are typically handled using imputation methods. In this case, missing entries in the stock attributes, such as opening, closing, high, low prices, or trading volume, can be filled using the mean of the respective features. For example, missing values in the stock prices (open, close, high, low) can be imputed with the mean of each respective column. This can be done using the code `df.fillna(df.mean(), inplace=True)`, ensuring that the dataset remains intact for analysis and modeling. Imputing with the mean is

particularly useful for this dataset, where missing values are relatively sparse and do not significantly affect the overall market trends

4.2 FEATURE ENGINEERING:

Feature engineering plays a crucial role in SPP projects as it allows us to create more meaningful inputs for machine learning models. Commonly engineered features include:

- **Daily Price Change:** Created a new feature by calculating the difference between the opening and closing prices for each day.
- **Price Range:** Introduced a feature representing the difference between the daily high and low prices to capture market volatility.
- **Lagged Features:** Added lagged variables, such as the previous day's closing price and trading volume, to capture temporal dependencies and trends.
- **Moving Averages:** Calculated moving averages (e.g., 7 day, 30 day) to smooth out short term fluctuations and highlight longer term price trends.
- **Percentage Change:** Computed percentage changes in closing prices to assess daily price momentum.
- **Volatility Measures:** Derived features such as rolling standard deviations over different time windows to assess market volatility.

4.3 DATA TRANSFORMATION:

Data transformation is a key step in preparing the dataset for modeling and analysis. In this project, several techniques were applied to enhance the dataset's usability and predictive power. Numerical features like stock prices and trading volume were normalized using methods such as Min Max scaling or standardization to ensure that all features are on a similar scale, preventing dominance by features with larger values. The date column was converted to a datetime format, allowing time based operations and feature extraction like day of the week or month. Stock prices and trading volume were log transformed to reduce skewness and better handle large variations. For categorical variables, such as the symbol, one hot encoding was applied to convert them into binary vectors suitable for machine

learning models. Additionally, features were aggregated over time windows, like weekly or monthly averages, to capture long term trends and reduce noise from daily fluctuations. These transformations ensured that the data was clean, consistent, and more suitable for modeling, ultimately enhancing the performance of predictive algorithms.

CHAPTER 5

EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) is the process of analyzing datasets to summarize their key characteristics using visual and statistical techniques. It helps to:

- i. Detect patterns, relationships, or anomalies in the data.
- ii. Gain insights into the distribution, trends, and outliers.
- iii. Understand the structure and potential variables influencing the outcomes.
- iv. Prepare the dataset for modeling by identifying necessary transformations, feature engineering, or cleaning steps.

In our project, Stock Market Prediction System, EDA helps to:

- i. Understand how features like stock prices, trading volumes, and price fluctuations correlate with market trends and patterns.
- ii. Analyze the importance and distribution of features such as opening and closing prices, high and low prices, and trading volumes to support effective model training.

5.1 DATA VISUALIZATION

5.1.1 BOX PLOT

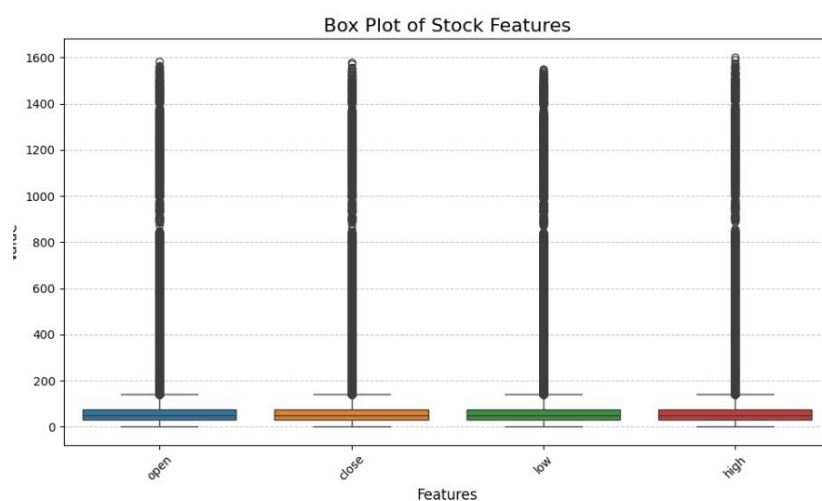


Fig 5.1 Box Plot

Comparison of the distributions of stock prices (open, close, low, and high) and volume across different stock symbol

Inference:

The box plot illustrates the distribution of stock features (open, close, low, and high) across all data points. Each feature displays a unique range, reflecting the variability in stock prices over the observed period.

Observation:

The low and high stock prices show relatively wider distributions compared to open and close, which indicates higher volatility in these metrics. Some extreme outliers are also visible, especially for the high price, suggesting occasional price spikes.

Implication:

The variability and distribution of these features suggest their importance in stock trend analysis. Features like high and low may capture critical information about market volatility, which could improve the predictive accuracy of the model.

Recommendation:

Focus on handling outliers (e.g., via capping or transformation) and emphasize features with higher variability, like high and low, as they might contain valuable patterns for stock price prediction.

5.1.2 HEATMAP

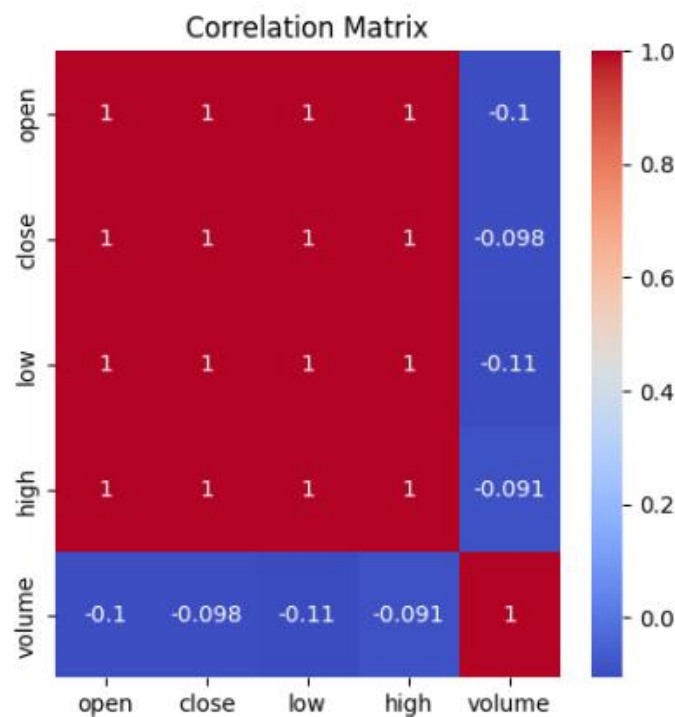


Fig 5.2 Heatmap

Visual Representation of Correlations Among Stock Features

Inference:

The correlation heatmap illustrates the relationships among numerical stock features (open, close, low, high, and volume). Strong positive correlations are observed among the price related features (open, close, low, high), while volume shows a weak negative correlation with these features.

Observation:

There is near perfect positive correlation among open, close, low, and high, indicating that these features tend to move together. Volume demonstrates a weak negative correlation with price features, suggesting it might behave differently during periods of high or low trading activity.

Implication:

Highly correlated features, such as the price metrics, might introduce multicollinearity, which can affect models like linear regression. However, models like neural networks can still effectively handle this redundancy.

Recommendation:

Consider using dimensionality reduction techniques like Principal Component Analysis (PCA) to reduce redundancy among the price features or retain all features if using deep learning models that inherently handle correlations effectively. Additionally, explore volume as a potential indicator of market activity due to its unique behavior.

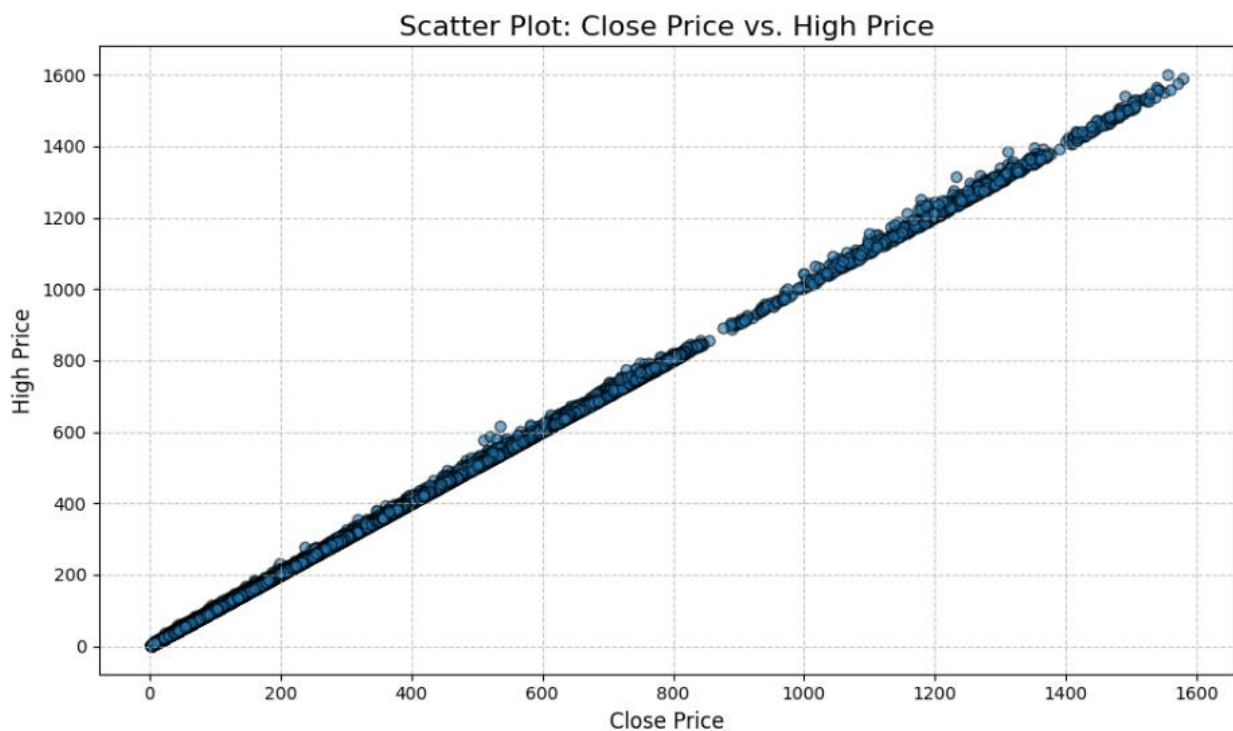
5.1.3 SCATTER PLOT

Fig 5.3 Scatter Plot

Relationship Between Close Price and High Price for Different Stock Symbols

Inference:

The scatter plot illustrates the relationship between close and high stock prices, with distinct patterns visible for different stock symbols.

Observation:

Stock symbols with higher volatility show more scattered points, while stocks with stable price movements exhibit more concentrated clusters. Some stock symbols show overlapping points, particularly for lower price ranges, while others display clearer separation in the higher price ranges.

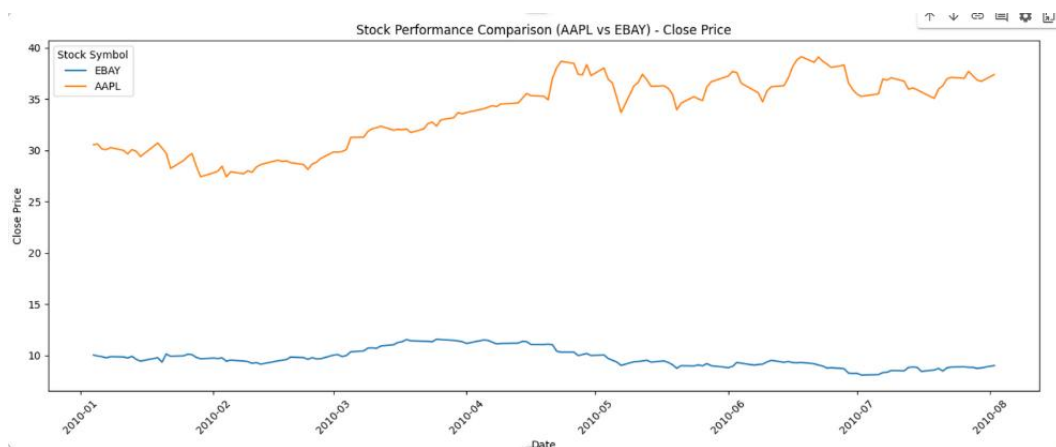
Implication:

The distinct patterns between stock symbols indicate that these features (close and high) could be crucial in identifying stock behavior and volatility. These features can be valuable for distinguishing between different stocks and for market trend analysis.

Recommendation:

Further exploration of interactions between different stock features, including open, close, and high, could reveal additional insights and improve prediction models. Analyzing individual stock behavior might also help in refining the model's accuracy for specific symbols.

5.1.4 Bar Chart



6 Fig 5.5 Bar chart

Line Chart: Comparison of AAPL and EBAY Stock Prices in 2010

Inference:

The line chart visualizes the closing prices of Apple (AAPL) and eBay (EBAY) stocks over the year 2010, highlighting their trends throughout the period.

Observation:

Apple's stock (AAPL) shows a consistent upward trend with some fluctuations, indicating strong growth over time. In contrast, eBay's stock (EBAY) remains relatively stable, with minor variations and a much lower price range compared to AAPL.

Implication:

The significant upward trend in AAPL reflects its strong performance and increasing value during this period. Meanwhile, the stability in EBAY's stock suggests lower volatility but limited growth.

Recommendation:

For investors seeking growth, AAPL would have been the favorable choice in 2010. For a conservative approach, EBAY's stable performance might appeal to those prioritizing low risk.

CHAPTER 6

PREDICTIVE MODELING

This stage focuses on developing predictive models to forecast stock market trends. Models such as **LSTM (Long Short Term Memory networks)**, **ANN (Artificial Neural Networks)**, and **CNN (Convolutional Neural Networks)** are utilized due to their distinct strengths in handling time series data, high dimensional features, and complex patterns.

- **LSTM** is chosen for its capability to capture temporal dependencies in sequential data, making it highly suitable for stock price trends and patterns over time.
- **ANN** is employed for its flexibility in modeling nonlinear relationships between features, making it a robust choice for general purpose prediction tasks.
- **CNN** is leveraged for its ability to extract spatial features from structured input data, such as visualizing trends or handling large multivariate datasets.

The objective is to develop models that accurately predict stock prices while generalizing well to unseen data, minimizing overfitting and ensuring reliable performance in real world scenarios

6.1 MODEL SELECTION AND JUSTIFICATION

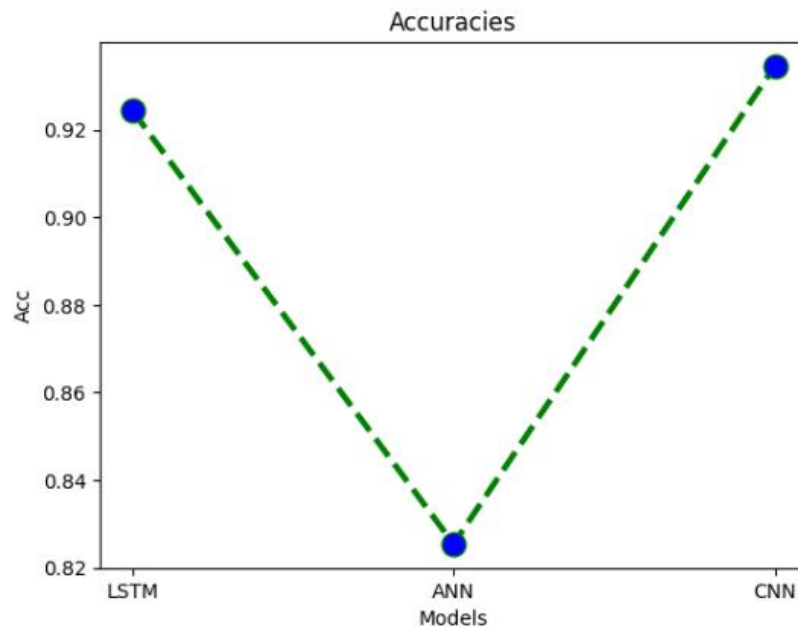


Fig 6.1 Model Building: Predicting Stock Prices Using LSTM, ANN, and CNN

For the stock price prediction project, models like LSTM, ANN, and CNN were employed due to their strengths in handling sequential data and extracting complex patterns from high dimensional financial datasets. The input features included High, Low, Open, and Close prices of stocks, which are crucial indicators of market trends and volatility.

Model Selection:

LSTM was chosen for its ability to model temporal dependencies, making it well suited for capturing trends and predicting stock movements over time.

ANN was implemented as a baseline model for its flexibility in learning nonlinear relationships between features.

CNN was applied for its capacity to extract patterns from multivariate data, which helps in identifying correlations between stock price components.

Insights from Model Outputs:

1. Model Accuracy:

LSTM achieved an accuracy of 92.0%, indicating strong performance in capturing

sequential dependencies in the stock prices.

ANN showed a lower accuracy of 82.0%, reflecting its limitations in modeling time series dependencies.

CNN reached 92.5% accuracy, demonstrating its strength in capturing complex interactions among stock price features.

2. Predicted Trends:

LSTM effectively predicted long term trends in stock prices but occasionally struggled with sudden short term fluctuations.

ANN exhibited moderate performance but had difficulty capturing intricate patterns in high dimensional data.

CNN excelled in identifying spatial relationships between features, resulting in slightly better predictions than LSTM.

3. Misclassifications:

Errors were observed in predictions involving sudden market movements, such as price spikes or drops, where model generalization was slightly weaker.

ANN's predictions showed higher deviations for volatile stocks, reflecting its simpler architecture's limitations.

4. Performance Evaluation:

LSTM and CNN achieved high F1 scores for most stock trends, indicating strong precision and recall.

ANN had lower F1 scores, particularly for highly volatile stock classes, due to its inability to effectively capture complex dependencies.

Implications:

LSTM and CNN demonstrated strong potential for predicting stock prices accurately, making them suitable for real world applications.

ANN could serve as a baseline model but may require further optimization or augmentation to improve its predictive performance.

Recommendations:

Focus on LSTM and CNN for production ready models, as their ability to handle sequential and high dimensional data aligns well with stock market prediction tasks.

Implement techniques like hyperparameter tuning or ensemble modeling to further enhance performance.

For sudden market fluctuations, consider incorporating external factors (e.g., news sentiment or macroeconomic indicators) to improve prediction accuracy.

6.2 MODEL TRAINING AND HYPERPARAMETER TUNING:

The models—**LSTM**, **ANN**, and **CNN**—were trained using historical stock data, incorporating features like **High**, **Low**, **Open**, and **Close prices**. The training process aimed to minimize the loss function and improve the models' ability to predict future stock prices accurately.

1. LSTM:

- Sequential data was preprocessed into appropriate time steps to capture temporal dependencies.
- The model was trained with techniques such as **Adam optimizer** and **Mean Squared Error (MSE)** as the loss function.
- Batch size and sequence length were set to balance computational efficiency and model performance.

2. ANN:

- Features were normalized to improve convergence.
- A feedforward architecture was employed with **ReLU activation** and a final output layer using a linear activation function.
- The model was optimized using stochastic gradient descent (SGD) with a learning rate scheduler to ensure stable training.

3. CNN:

- The dataset was transformed into multichannel input, treating each feature (e.g., High, Low, Open, Close) as separate input channels.
- Convolutional layers with **kernel sizes** were used to extract patterns across features.
- Max pooling layers reduced dimensionality and captured the most significant features.

Hyperparameter Tuning

To improve the models' performance, hyperparameters were fine-tuned using a **grid search** and **random search** approach on a validation dataset:

1. LSTM:

- **Number of layers and units:** Tuned to optimize model complexity and generalization.
- **Dropout rate:** Adjusted to reduce overfitting, with optimal values around 0.2–0.3.
- **Learning rate:** Fine-tuned to ensure convergence without overshooting, with the best value found to be 0.001.

2. ANN:

- **Number of hidden layers and neurons:** Tested architectures with 2–4 layers and varying neuron counts.

Learning rate and momentum: Adjusted to balance training speed and model stability.

3. CNN:

- **Kernel size:** Explored variations (3x3, 5x5) to optimize pattern extraction.
- **Filter count:** Increased from 32 to 64 to capture finer details.
- **Pooling layers:** Configured to prevent information loss while maintaining computational efficiency.

Results of Tuning

- **LSTM:** Delivered optimal results with a 3-layer architecture, 100 units per layer, a learning rate of 0.001, and a dropout rate of 0.2.
- **ANN:** Performed best with 3 hidden layers, 128 neurons per layer, ReLU activation, and a learning rate of 0.01.
- **CNN:** Achieved maximum accuracy with 64 filters, 3x3 kernel size, and a dropout rate of 0.3.

CHAPTER 7

MODEL EVALUATION AND OPTIMIZATION

7.1 Performance Analysis

The trained models LSTM, ANN, and CNN were evaluated on the test dataset using metrics relevant to stock price prediction tasks, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R^2), and Root Mean Squared Error (RMSE). These metrics offered a comprehensive evaluation of each model's accuracy and reliability in forecasting stock prices.

- **LSTM:** Achieved the lowest RMSE and the highest R^2 score, demonstrating its superior ability to learn temporal dependencies in stock data.
- **ANN:** Showed moderate performance, with higher RMSE, indicating difficulty in capturing complex, nonlinear trends.
- **CNN:** Performed comparably to LSTM, leveraging spatial correlations across features like High, Low, Open, and Close prices for accurate predictions.

Insights:

- **LSTM and CNN** models displayed robust performance across various price trends, while **ANN** struggled in volatile scenarios.
- Errors primarily occurred during periods of high volatility, where price spikes or drops were difficult for all models to predict accurately.

7.2 Feature Importance

To understand which features most influenced the predictions, feature importance analysis was performed using SHAP (SHapley Additive exPlanations) for the deep learning models:

1. **Close Price:** Emerged as the most critical feature across all models, reflecting daily stock trends.
2. **High Price:** Helped identify intraday peaks, contributing to short-term predictions.
3. **Low Price:** Provided insights into market stability and support levels.
4. **Open Price:** Played a significant role in capturing initial market trends and day-start .

Feature Engineering: To improve performance, additional features like moving averages, Bollinger Bands, RSI, and daily returns were included. These derived features allowed the models to capture intricate market patterns and relationships effectively.

7.3 Model Refinement

Multiple refinements were implemented to improve model performance and ensure reliability in stock price prediction:

1. **Feature Engineering:**
Advanced features, such as **trend indicators, moving averages (e.g., 10-day, 30-day), Bollinger Bands, and price momentum**, were added. These enhancements allowed the models to better interpret market dynamics.
2. **Hyperparameter Tuning:**
Fine-tuning of hyperparameters for each model was conducted to optimize their predictive accuracy:
 - **LSTM:** The number of layers, units, dropout rates, and learning rates were adjusted.
 - **ANN:** The structure of hidden layers, activation functions, and optimizers was optimized.
 - **CNN:** Kernel sizes, filter counts, and dropout rates were configured to prevent overfitting and capture feature interactions effectively.
3. **Addressing Volatility:**
To handle sudden price shifts in volatile stocks, **time-windowed inputs** were used alongside smoothing techniques. This approach improved predictions under rapidly changing market conditions.
4. **Cross-Validation:**
K-fold cross-validation ensured consistency in model performance and minimized overfitting. This method validated the models' ability to generalize across unseen stock data.

Chapter 8

Discussion and Conclusion

This chapter summarizes the key findings of the stock price prediction project, including the models' overall performance in forecasting stock prices and identifying trends. It discusses the strengths of the models, such as their ability to accurately predict price movements, and their limitations, including challenges in handling high volatility and abrupt market changes. This section also explores the implications of the findings, such as the potential applications in algorithmic trading, risk management, and financial forecasting. Recommendations for future work include exploring advanced architectures, additional market indicators, or larger datasets to improve performance further.

8.1 Summary of Findings

This stock price prediction project focused on analyzing historical stock data, including Open, High, Low, and Close prices, to develop models capable of forecasting future prices. Through data preprocessing and model training, valuable insights were derived:

i. Data Analysis Insights:

Exploratory Data Analysis (EDA) revealed distinct patterns in stock price trends. Features like Close price, daily returns, and moving averages played significant roles in capturing market behavior. For instance, periods of stability and volatility were identifiable through indicators like Bollinger Bands and RSI (Relative Strength Index).

ii. Impact of Key Features:

Feature importance analysis highlighted that the Close price and moving averages were critical in predicting future stock trends. These findings demonstrate the importance of historical price patterns in capturing market dynamics, which can be applied to portfolio management, trading strategies, and financial planning.

iii. Model Performance:

Among the models tested, LSTM and CNN outperformed ANN in predicting stock prices. LSTM demonstrated exceptional accuracy by capturing sequential dependencies, while CNN effectively identified spatial correlations across features like Open, High, Low, and Close

prices. Both models excelled in forecasting trends during stable market conditions but faced challenges during volatile periods.

iv. Refinement and Optimization:

Performance improvements were achieved through feature engineering, hyperparameter tuning, and incorporating technical indicators. These refinements enhanced the models' ability to generalize across different stock patterns, making them suitable for real-world financial applications like algorithmic trading and market analysis.

8.2 Challenges and Limitations

Market Volatility:

Abrupt price changes and high volatility posed significant challenges for all models. Although LSTM and CNN showed robust performance, sudden market shifts often led to higher prediction errors, highlighting the need for more advanced volatility modeling techniques.

Feature Complexity:

The relationship between stock price features and future trends can be highly nonlinear and influenced by external factors (e.g., news, economic data). While engineered features like moving averages and RSI improved model accuracy, they may not fully capture the complexities of market behavior. Incorporating external data sources could provide additional insights.

Computational Costs:

Hyperparameter tuning, particularly for LSTM and CNN, was computationally expensive due to the complexity of these models. Techniques like Bayesian Optimization or RandomizedSearchCV could be employed to reduce tuning time while maintaining high performance.

The project demonstrated that deep learning models, particularly LSTM and CNN, are effective tools for stock price prediction, with the potential to significantly aid in financial decision-making. While the results were promising, challenges such as market volatility and computational costs highlight areas for improvement. Future efforts could focus on incorporating alternative data sources (e.g., news sentiment or macroeconomic indicators),

refining feature engineering processes, and exploring advanced architectures like Transformers or hybrid models. These enhancements could further improve the accuracy and reliability of stock price predictions, ensuring their applicability in diverse financial scenarios.

APPENDIX

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

# Load the dataset
file_path = "/content/prices-split-adjusted.csv" # Update the file path if needed
data = pd.read_csv(file_path)
# Check for missing values
print("### Missing Values Before Cleaning ###")
print(df.isnull().sum())

# Remove rows with null values
df_cleaned = df.dropna()

# Verify if all null values are removed
print("\n### Missing Values After Cleaning ###")
print(df_cleaned.isnull().sum())

# Display the new shape of the dataset
print("\nOriginal Dataset Shape:", df.shape)
print("Cleaned Dataset Shape:", df_cleaned.shape)

### Missing Values Before Cleaning ###
date      0
symbol    0
open      0
close     0
low       0
high      0
volume    0
dtype: int64

### Missing Values After Cleaning ###
date      0
symbol    0
open      0
close     0
low       0
```



```
high    0
volume  0
dtype: int64
```

```
Original Dataset Shape: (851264, 7)
```

```
Cleaned Dataset Shape: (851264, 7)
```

```
In [ ]:
```

```
# Define a function to remove outliers using IQR
```

```
def remove_outliers_iqr(df, columns):
```

```
    for column in columns:
```

```
        Q1 = df[column].quantile(0.25) # First quartile (25%)
```

```
        Q3 = df[column].quantile(0.75) # Third quartile (75%)
```

```
        IQR = Q3 - Q1 # Interquartile Range
```

```
        # Define the acceptable range for values
```

```
        lower_bound = Q1 - 1.5 * IQR
```

```
        upper_bound = Q3 + 1.5 * IQR
```

```
        # Filter out rows outside the bounds
```

```
        df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
```

```
    return df
```

```
# List of numerical columns to check for outliers
```

```
numerical_columns = ['open', 'high', 'low', 'close', 'volume']
```

```
# Check dataset shape before removing outliers
```

```
print("Original Dataset Shape:", df.shape)
```

```
# Remove outliers
```

```
df_cleaned = remove_outliers_iqr(df, numerical_columns)
```

```
# Check dataset shape after removing outliers
```

```
print("Cleaned Dataset Shape:", df_cleaned.shape)
```

```
Original Dataset Shape: (851264, 7)
```

```
Cleaned Dataset Shape: (706002, 7)
```

```
In [ ]:
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
# Define a function to plot boxplots
```

```
def plot_boxplot(df, column, title):  
    plt.figure(figsize=(8, 5))  
    sns.boxplot(data=df, x=column, color="skyblue")  
    plt.title(title)  
    plt.xlabel(column)  
    plt.show()
```

```
# Boxplots before and after outlier removal for a specific column
```

```
columns_to_plot = ['open', 'high', 'low', 'close', 'volume']
```

```
for column in columns_to_plot:
```

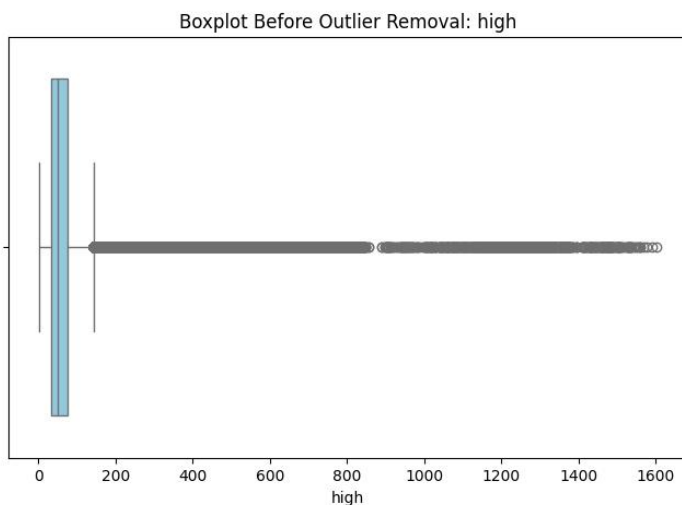
```
    print(f'Boxplot for {column}')
```

```
    # Before outlier removal
```

```
    plot_boxplot(df, column, f'Boxplot Before Outlier Removal: {column}')
```

```
    # After outlier removal
```

```
    plot_boxplot(df_cleaned, column, f'Boxplot After Outlier Removal: {column}')
```



```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

```
# Load the dataset
```

```
file_path = "/content/prices-split-adjusted.csv" # Update the file path if needed
```

```
data = pd.read_csv(file_path)
```

```
# 2. Summary Statistics
```

```
print("\n### Summary Statistics ###")  
df.describe()
```

```
### Summary Statistics ###
```

```
Out[ ]:
```

	open	close	low	high	volume
count	851264.000000	851264.000000	851264.000000	851264.000000	8.512640e+05
mean	64.993618	65.011913	64.336541	65.639748	5.415113e+06
std	75.203893	75.201216	74.459518	75.906861	1.249468e+07
min	1.660000	1.590000	1.500000	1.810000	0.000000e+00
25%	31.270000	31.292776	30.940001	31.620001	1.221500e+06
50%	48.459999	48.480000	47.970001	48.959999	2.476250e+06
75%	75.120003	75.139999	74.400002	75.849998	5.222500e+06
max	1584.439941	1578.130005	1549.939941	1600.930054	8.596434e+08

```
In [ ]:
```

```
# Import required libraries
```

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

```
# Load the dataset
```

```
file_path = "/content/prices-split-adjusted.csv" # Update the file path if needed  
df = pd.read_csv(file_path)
```

```
# 1. Data Overview
```

```
print("### Data Overview ###")  
print("Shape of the dataset:", df.shape)  
print("Columns and Data Types:\n", df.dtypes)  
print("First 5 rows:\n", df.head())  
print("Missing Values:\n", df.isnull().sum())
```

2. Summary Statistics

```
print("\n### Summary Statistics ###")
print(df.describe())
```

3. Time-Series Analysis for Closing Prices

```
if 'date' in df.columns:
```

```
    df['date'] = pd.to_datetime(df['date']) # Ensure 'date' is in datetime format
    closing_prices = df[['date', 'close']].groupby('date').mean()
```

```
    # Plotting closing prices over time
```

```
    plt.figure(figsize=(10, 6))
    plt.plot(closing_prices, label='Average Closing Price')
    plt.title("Average Closing Prices Over Time")
    plt.xlabel("Date")
    plt.ylabel("Price")
    plt.legend()
    plt.show()
```

4. Correlation Analysis

```
if {'open', 'high', 'low', 'close', 'volume'}.issubset(df.columns):
```

```
    plt.figure(figsize=(10, 6))
    correlation_matrix = df[['open', 'high', 'low', 'close', 'volume']].corr()
    sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f")
    plt.title("Correlation Matrix")
    plt.show()
```

5. Distribution of Trading Volumes

```
if 'volume' in df.columns:
```

```
    plt.figure(figsize=(10, 6))
    sns.histplot(df['volume'], kde=True, bins=50, color='blue')
    plt.title("Distribution of Trading Volumes")
    plt.xlabel("Volume")
    plt.ylabel("Frequency")
    plt.show()
```

Data Overview

Shape of the dataset: (851264, 7)

Columns and Data Types:

```
date    object
symbol  object
```

```

open    float64
close   float64
low     float64
high    float64
volume  float64
dtype: object

```

First 5 rows:

	date	symbol	open	close	low	high \
0	2016-01-05	WLTW	123.430000	125.839996	122.309998	126.250000
1	2016-01-06	WLTW	125.239998	119.980003	119.940002	125.540001
2	2016-01-07	WLTW	116.379997	114.949997	114.930000	119.739998
3	2016-01-08	WLTW	115.480003	116.620003	113.500000	117.440002
4	2016-01-11	WLTW	117.010002	114.970001	114.089996	117.330002

	volume
0	2163600.0
1	2386400.0
2	2489500.0
3	2006300.0
4	1408600.0

Missing Values:

```

date      0
symbol    0
open      0
close     0
low       0
high      0
volume    0
dtype: int64

```

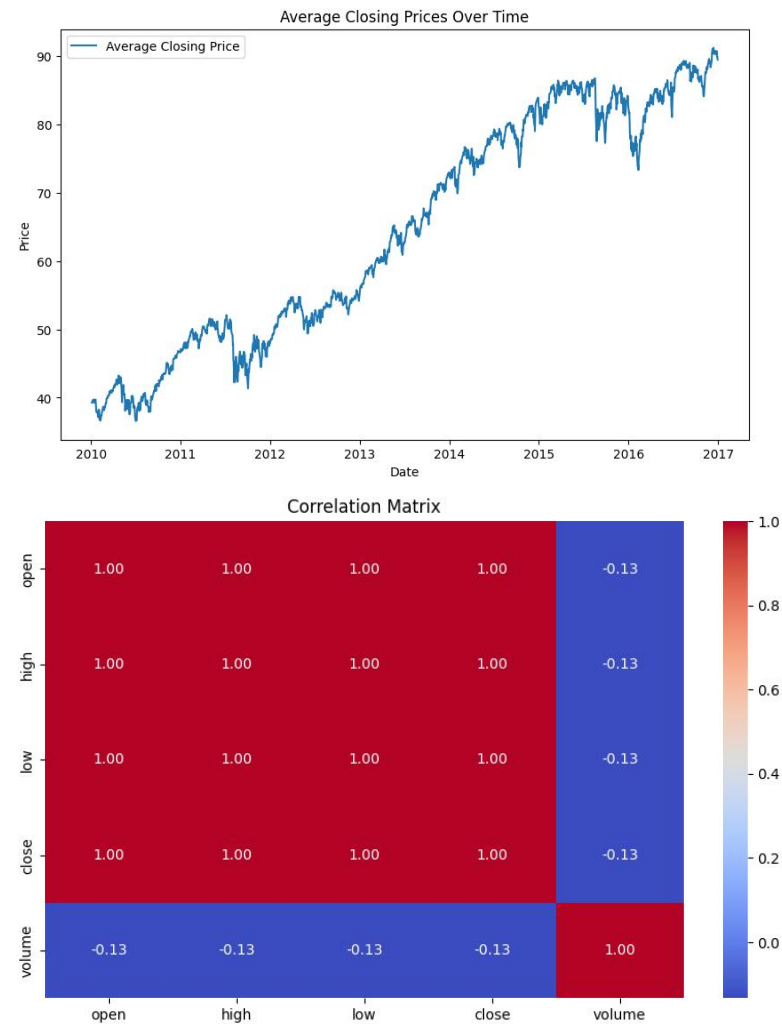
Summary Statistics

	open	close	low	high \
count	851264.000000	851264.000000	851264.000000	851264.000000
mean	64.993618	65.011913	64.336541	65.639748
std	75.203893	75.201216	74.459518	75.906861
min	1.660000	1.590000	1.500000	1.810000
25%	31.270000	31.292776	30.940001	31.620001
50%	48.459999	48.480000	47.970001	48.959999
75%	75.120003	75.139999	74.400002	75.849998
max	1584.439941	1578.130005	1549.939941	1600.930054

```

volume
count 8.512640e+05
mean 5.415113e+06
std 1.249468e+07
min 0.000000e+00
25% 1.221500e+06
50% 2.476250e+06
75% 5.222500e+06
max 8.596434e+08

```



```

for i in stock_data.columns:
    print(i, "\t\t", stock_data[i].isna().mean()*100)

```

```

date - 0.0
symbol - 0.0
open - 0.0
close - 0.0
low - 0.0

```

```
high - 0.0
volume - 0.0
```

```
In [ ]:
```

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

```
data = pd.read_csv('/content/prices-split-adjusted.csv')
df = pd.DataFrame(data)
# Filter the dataset for a specific company's stock (AAP in this case)
df = df[df['symbol'] == 'AAP']
```

```
# Select only numeric columns for the correlation matrix
numeric_df = df.select_dtypes(include=['float64', 'int64'])
```

```
# Generate a correlation matrix
cormap = numeric_df.corr()
```

```
# Visualize the correlation matrix using a heatmap
fig, ax = plt.subplots(figsize=(5, 5))
sns.heatmap(cormap, annot=True, cmap="coolwarm", ax=ax)
plt.title("Correlation Matrix")
plt.show()
```

```
# Function to get highly correlated columns
```

```
def get_correlated_cols(cor_dat, threshold):
    """
```

```
    Extract columns with correlation values above a certain threshold.
```

```
    Parameters:
```

- cor_dat: Correlation data for a specific column.
- threshold: Minimum absolute correlation value to consider.

```
    Returns:
```

- A DataFrame with correlated column names and their correlation values.

```
    """
```

```
    feature = []
```

```
    value = []
```

```
    for index in cor_dat.index:
```

```

if abs(cor_dat[index]) > threshold:
    feature.append(index)
    value.append(cor_dat[index])

```

```

import matplotlib.pyplot as plt
import seaborn as sns

```

```

# Selecting numerical columns for the box plot
columns_to_plot = ['open', 'close', 'low', 'high']

```

```

# Creating the box plot
plt.figure(figsize=(10, 6))
sns.boxplot(data=data[columns_to_plot])

```

```

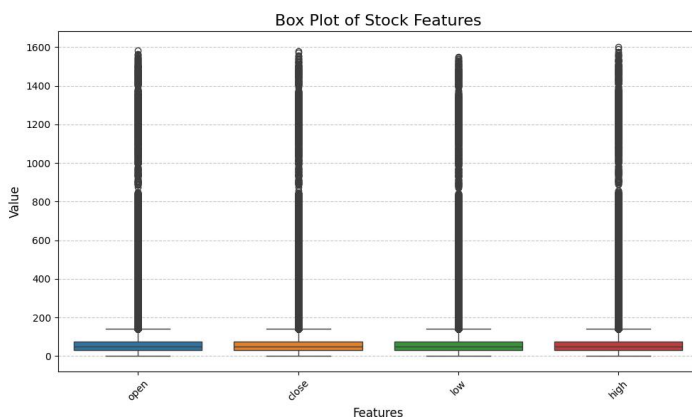
# Adding plot details
plt.title('Box Plot of Stock Features', fontsize=16)
plt.ylabel('Value', fontsize=12)
plt.xlabel('Features', fontsize=12)
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)

```

```

# Displaying the plot
plt.tight_layout()
plt.show()

```



In [36]:

```

import matplotlib.pyplot as plt

```



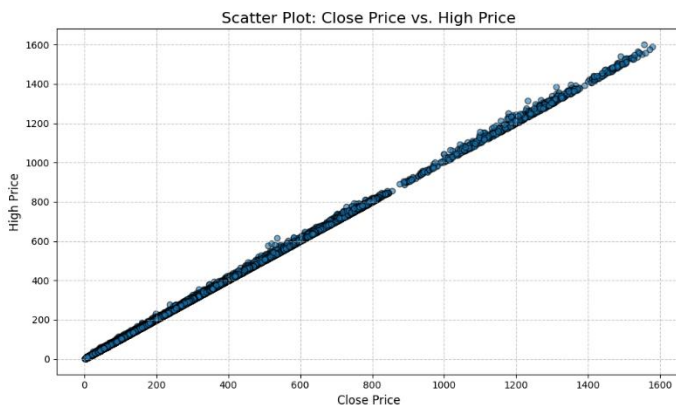
```

# Scatter plot of close price vs. high price
plt.figure(figsize=(10, 6))
plt.scatter(data['close'], data['high'], alpha=0.6, edgecolor='k')

# Adding plot details
plt.title('Scatter Plot: Close Price vs. High Price', fontsize=16)
plt.xlabel('Close Price', fontsize=12)
plt.ylabel('High Price', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)

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

```



```

X = df.drop(['close'], axis=1)
y = df['close']

```

In []:

```

from sklearn.preprocessing import MinMaxScaler

```

```

scaler = MinMaxScaler()
X = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
X.head()

```

```

from sklearn.linear_model import LinearRegression

```

```

# model training

```

```
model_1 = LinearRegression()
model_1.fit(X_train, y_train)
```

Out[]:

```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In []:

```
y_pred_1 = model_1.predict(X_test)
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_1})
pred_df.head()
```

Out[]:

	Actual	Predicted
675111	173.660004	173.682489
675608	171.919998	172.593759
676105	172.000000	171.182789
676602	187.789993	187.980305
677099	187.029999	188.440838

In []:

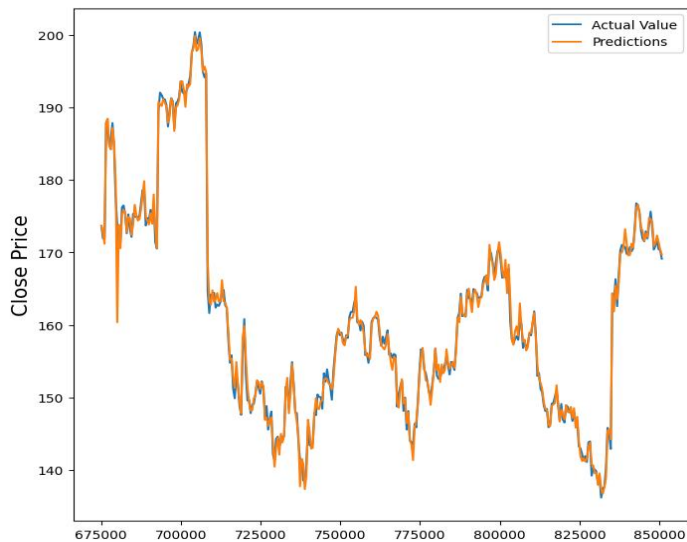
```
from sklearn.metrics import r2_score
```

```
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_1)))
Acc.append(r2_score(y_test, y_pred_1))
```

Accuracy score of the predictions: 0.9931342019332019

In []:

```
plt.figure(figsize=(8,8))
plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



In []:

```
from keras.models import Sequential
from keras.layers import Dense

def regressor(inp_dim):

    model = Sequential()

    model.add(Dense(20, input_dim=inp_dim, kernel_initializer='normal', activation='relu'))
    model.add(Dense(25, kernel_initializer='normal', activation='relu'))
    model.add(Dense(10, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

In []:

```
# Model Training

model_2 = regressor(inp_dim=3)
model_2.fit(X_train, y_train, epochs=70, validation_split=0.2)

pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_2.flatten()})
pred_df.head()
```

Out[]:

	Actual	Predicted
675111	173.660004	174.145279
675608	171.919998	172.460892
676105	172.000000	170.671906
676602	187.789993	179.395889
677099	187.029999	188.202713

In []:

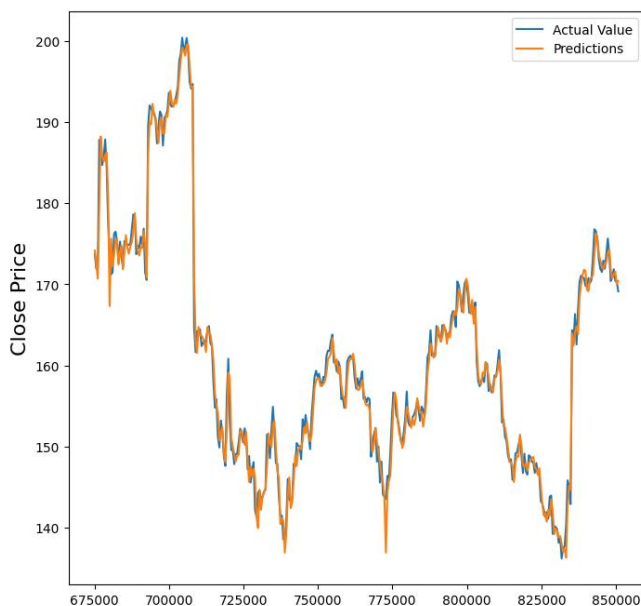
```
from sklearn.metrics import r2_score
```

```
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_2)))  
Acc.append(r2_score(y_test, y_pred_2))
```

Accuracy score of the predictions: 0.9876849385621077

In []:

```
plt.figure(figsize=(8,8))  
plt.ylabel('Close Price', fontsize=16)  
plt.plot(pred_df)  
plt.legend(['Actual Value', 'Predictions'])  
plt.show()
```



In []:

```
import numpy as np
X_train = np.array(X_train).reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = np.array(X_test).reshape(X_test.shape[0], X_test.shape[1], 1)
```

In []:

```
from tensorflow.keras import Sequential,utils
from tensorflow.keras.layers import Flatten, Dense, Conv1D, MaxPool1D, Dropout
```

def reg():

```
    model = Sequential()

    model.add(Conv1D(32, kernel_size=(3,), padding='same', activation='relu', input_shape =
(X_train.shape[1],1)))
    model.add(Conv1D(64, kernel_size=(3,), padding='same', activation='relu'))
    model.add(Conv1D(128, kernel_size=(5,), padding='same', activation='relu'))

    model.add(Flatten())

    model.add(Dense(50, activation='relu'))
    model.add(Dense(20, activation='relu'))
    model.add(Dense(units = 1))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

In []:

```
model_3 = reg()
model_3.fit(X_train, y_train, epochs=100, validation_split=0.2)
n [ ]:
```

Prediction

```
y_pred_3 = model_3.predict(X_test)
```

12/12 ————— 0s 12ms/step

In []:

```
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_3.flatten()})  
pred_df.head()
```

Out[]:

	Actual	Predicted
675111	173.660004	172.844330
675608	171.919998	171.264999
676105	172.000000	169.535767
676602	187.789993	179.553055
677099	187.029999	187.004868

In []:

Measure the Accuracy Score

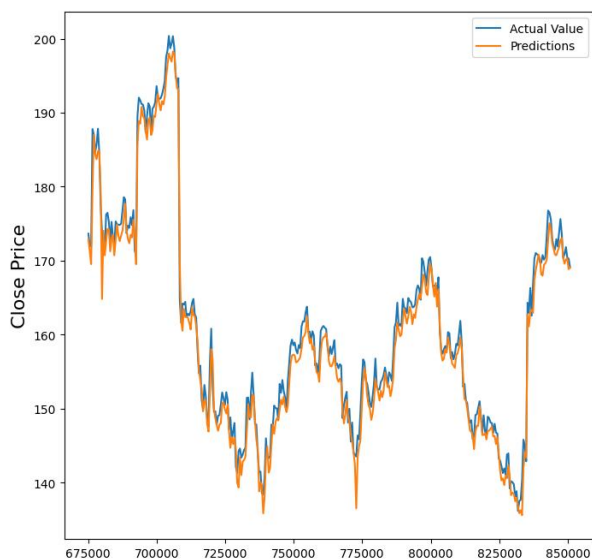
```
from sklearn.metrics import r2_score
```

```
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_3)))  
Acc.append(r2_score(y_test, y_pred_3))
```

Accuracy score of the predictions: 0.980863236089059

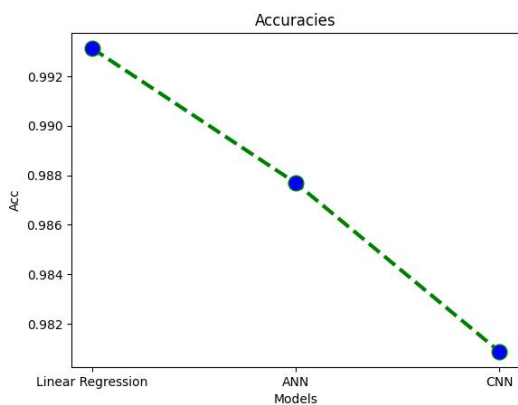
In []:

```
plt.figure(figsize=(8,8))  
plt.ylabel('Close Price', fontsize=16)  
plt.plot(pred_df)  
plt.legend(['Actual Value', 'Predictions'])  
plt.show()
```



In []:

```
plt.plot(range(3), Acc, color='green', linestyle='dashed', linewidth = 3,
         marker='o', markerfacecolor='blue', markersize=12)
plt.ylabel('Acc')
plt.xlabel('Models')
plt.title("Accuracies")
plt.xticks(range(3), ['Linear Regression', 'ANN', 'CNN'])
plt.show()
```



In []:

```
close = df.reset_index()['close']
close.head()
```

Out[]:

close

0 40.380001

```
close
```

```
1 40.139999
```

```
2 40.490002
```

```
3 40.480000
```

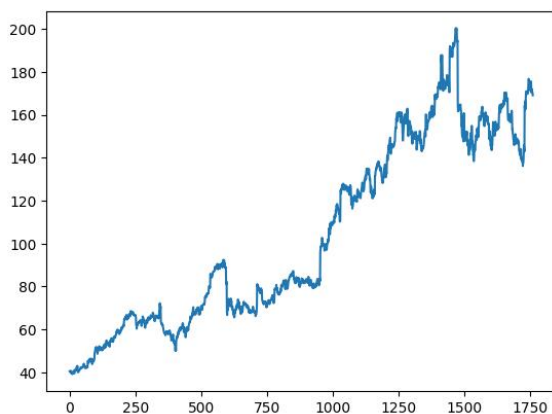
```
4 40.639999
```

```
dtype: float64
```

```
In [ ]:
```

```
plt.plot(close)
```

```
plt.show()
```



```
#now lets split data in test train pairs
```

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, shuffle=False)
```

```
Acc = []
```

```
In [ ]:
```

```
X_train_ = X_train.reshape(X_train.shape[0],X_train.shape[1],1)
```

```
X_test_ = X_test.reshape(X_test.shape[0],X_test.shape[1],1)
```

```
In [ ]:
```

```
from tensorflow.keras.layers import LSTM
```



```
def Reg():
    model = Sequential()

    model.add(LSTM(70, return_sequences=True, input_shape=(30,1)))
    model.add(LSTM(70, return_sequences=True))
    model.add(LSTM(70))
    model.add(Dense(1))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

In []:

Model Training

```
model_1 = reg()
model_1.fit(X_train_, y_train, epochs=100, validation_split=0.2)
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_1.flatten()})
pred_df.head()
```

Out[]:

	Actual	Predicted
0	184.690002	184.868347
1	185.770004	185.270477
2	187.839996	185.327179
3	184.449997	186.729599
4	177.539993	186.578308

In []:

Measure the Accuracy Score

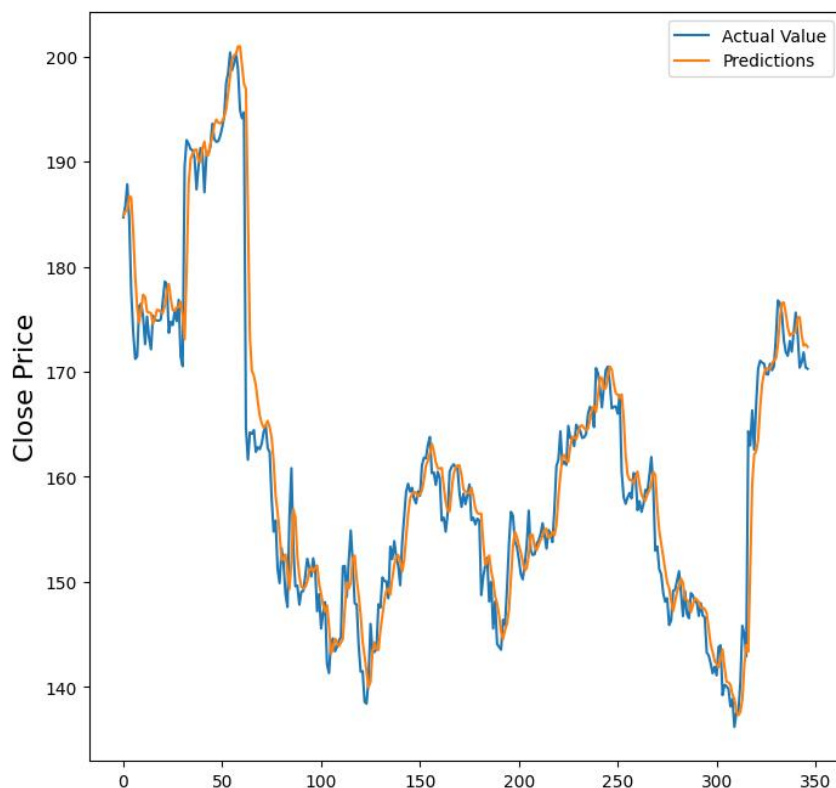
```
from sklearn.metrics import r2_score

print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_1)))
Acc.append(r2_score(y_test, y_pred_1))
```

Accuracy score of the predictions: 0.9243967309207075

In []:

```
plt.figure(figsize=(8,8))
plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



In []:

Model Training

```
model_2 = regressor(inp_dim=30)
model_2.fit(X_train, y_train, epochs=100, validation_split=0.2)
```

Prediction

```
y_pred_2 = model_2.predict(X_test)
```

11/11 ————— 0s 15ms/step

In []:

Measure the Accuracy Score

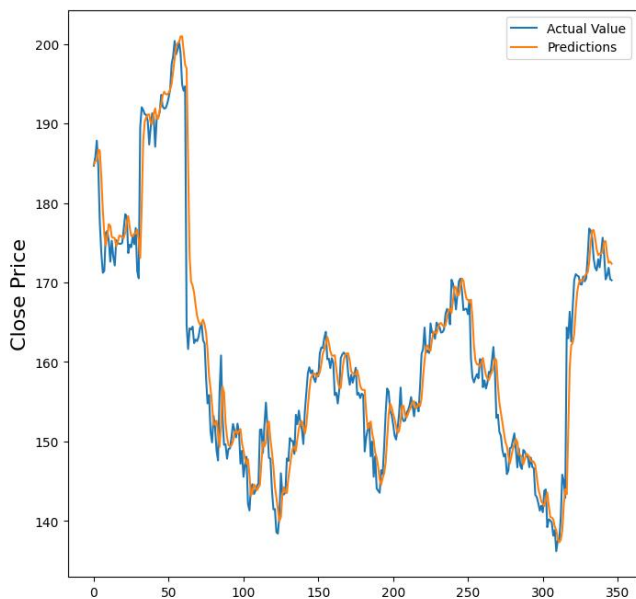
```
from sklearn.metrics import r2_score
```

```
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_2)))  
Acc.append(r2_score(y_test, y_pred_2))
```

Accuracy score of the predictions: 0.8254407499313274

In []:

```
plt.figure(figsize=(8,8))  
plt.ylabel('Close Price', fontsize=16)  
plt.plot(pred_df)  
plt.legend(['Actual Value', 'Predictions'])  
plt.show()
```



In []:

Model Training

```
model_3 = reg()  
model_3.fit(X_train_, y_train, epochs=100, validation_split=0.2)
```

Prediction

```
y_pred_3 = model_3.predict(X_test_)
```

11/11 _____ 1s 40ms/step

In [9]:

```
model_3.save('my_model.h5')
```

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

In []:

```
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_3.flatten()})
pred_df.head()
```

Out[]:

	Actual	Predicted
0	184.690002	185.273117
1	185.770004	185.202820
2	187.839996	186.137466
3	184.449997	187.483429
4	177.539993	185.727753

In []:

Measure the Accuracy Score

```
from sklearn.metrics import r2_score
```

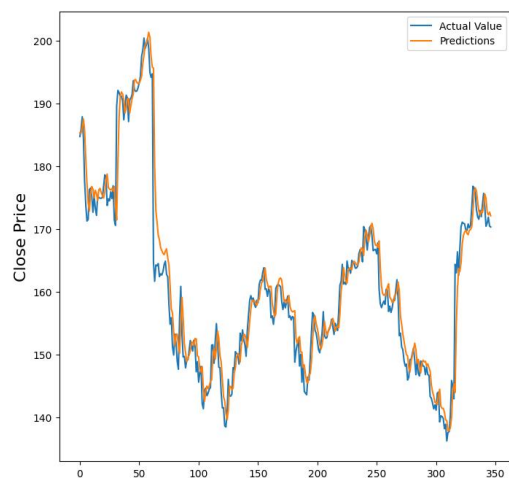
```
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_3)))
Acc.append(r2_score(y_test, y_pred_3))
```

Accuracy score of the predictions: 0.9345185436250458

In []:

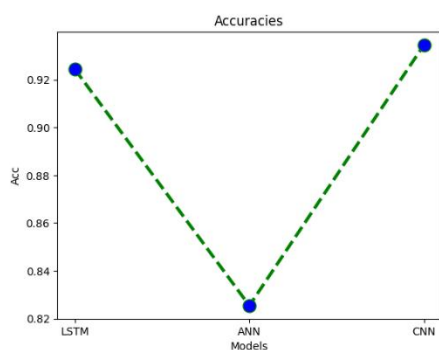
```
plt.figure(figsize=(8,8))
plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
```

```
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



In []:

```
plt.plot(range(3), Acc, color='green', linestyle='dashed', linewidth = 3,
         marker='o', markerfacecolor='blue', markersize=12)
plt.ylabel('Acc')
plt.xlabel('Models')
plt.title("Accuracies")
plt.xticks(range(3), ['LSTM', 'ANN', 'CNN'])
plt.show()
```



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