Chapter 1: Introduction

In the ever-evolving landscape of financial markets, the ability to predict stock prices accurately is a pursuit that combines data science, machine learning, and behavioral economics. This project represents a comprehensive exploration of stock price prediction by integrating cutting-edge technologies. The key components include Long Short-Term Memory (LSTM) networks, Game Theory-based biases, and Sentimental Analysis of news headlines, all powered by data fetched exclusively from the Yahoo Finance API.

The foundation of this project rests on the Yahoo Finance API, a robust and reliable source for financial data. The dataset comprises daily and intraday closing prices, enabling a granular examination of market trends. By leveraging this API, we ensure the consistency and accuracy of our data, fostering an environment conducive to insightful analysis.

LSTM: Learning Intrinsic Statistical Trends
The Long Short-Term Memory (LSTM) network, a variant of Recurrent Neural Networks (RNN), serves as the backbone of our predictive model. LSTM excels in capturing intricate patterns within time series data, making it an ideal choice for discerning the intrinsic statistical trends present in the historical stock prices.

Game Theory-Based Bias: Assessing Risk and Speculator Behavior:
Introducing a novel dimension to our predictive model, we incorporate Game Theory-based biases. These biases are derived from speculators' optimal strategies, determined by assessing the risk appetite of the market. By gauging whether it's opportune to take risks, our model provides insights into how speculators' decisions influence stock market behavior.

Sentimental Analysis: News Headlines Impact:
Recognizing the impact of external factors, we delve into Sentimental Analysis of news headlines associated with the stocks in our dataset. By scraping headlines and performing sentiment analysis, we gauge the broader market sentiment. The resulting bias is an indicator of how external news influences stock prices, thereby offering a holistic view of market dynamics.

Sentimental Analysis: Major event biases:
In addition to stock-specific news, our project recognizes the broader influence of major global events on market dynamics. This section focuses on incorporating the sentiment biases arising from significant occurrences like the COVID-19 pandemic, employee layoffs, and geopolitical conflicts such as the Russia-Ukraine war and the Israel-Hamas conflict. The goal is to understand how these major events shape overall market sentiments and subsequently influence stock prices.

Chapter 2: Literature Survey

The Game Theory, a mathematical and economic discipline, has emerged as a pivotal tool in various fields, with financial markets being a notable application. This framework provides a structured approach to analyzing strategic interactions among rational decision-makers. In financial markets, understanding decision-making processes becomes crucial, involving investors, speculators, and other participants. The paper under consideration develops a decision model rooted in Game Theory principles, aiming to offer insights into optimal strategies within financial markets. The foundational aspect of this decision model lies in comprehending the log return(rt) accompanied by a percentage change transformation (Wt). This transformation enhances the robustness of analyses, particularly regarding price changes, which play a central role in financial markets.

$$W_T = \prod_{t=1}^{T}(1+R_t) \iff \log W_T = \sum_{t=1}^{T} r_t, \qquad r_t = log(1+R_t) = logW_t - logW_{t-1}.$$

Figure 1: Log return function

Strategic decision-making is at the core of the Game Theory application, where investors and speculators are presented with choices - More Risk (MR), Less Risk (LR), and Not Play (NP). The probabilities associated with these choices (P(MR), P(LR), P(NP) form the essence of the decision model. Importantly, these probabilities are subject to the constraint that their summation equals 1. (P(MR) + P(LR) + P(NP) = 1)

		Speculator	
	\	More Risk (R^+)	Less Risk (R^-)
Market	Zero Adversity (0_A)	Profit	Profit
	Minor Adversity (m_A)	Profit	Small Loss
	Major Adversity (M_A)	Large Loss	Small Loss

Figure 2: Market vs Speculator

The paper emphasizes the probabilistic nature of these choices, reflective of the inherent uncertainty in financial markets. It underscores the significance of considering these probabilities to formulate adaptive and nuanced strategies that align with market conditions and an individual's risk appetite.

The optimal strategy arises from the evaluation of these probabilities in the prevailing market scenario. The paper positions the Game Theory-based decision model against traditional time series methods and a specially designed Markov Chain approach. This comparative analysis aims to assess the effectiveness, accuracy, and adaptability of the Game Theory model in predicting market behaviors.

In conclusion, the integration of Game Theory into financial modeling signifies a departure from deterministic approaches, recognizing the dynamic and uncertain nature of markets. By incorporating strategic decision-making under uncertainty, the model contributes to a more comprehensive understanding of market dynamics, offering a fresh perspective for investors and researchers. [1].

The paper begins by introducing game theory and its potential applications in finance. The authors argue that game theory can be used to model strategic interactions between market participants, such as in takeover contests or in the pricing of financial assets. They also note that game theory can help to address issues of asymmetric information, which is a common feature of financial markets. The authors then provide a brief overview of the literature on takeovers, which has been an important area of research in finance. They discuss how game theory has been used to model takeover contests and to explain why defensive measures taken by target firms may be optimal for their shareholders. They also note that game theory has been central to the literature on takeovers due to the strategic interactions and asymmetric information involved. Next, the authors discuss the literature on market microstructure, which is the study of the process and outcomes of exchanging assets under explicit trading rules. They note that game theory has been used to model the process of price formation in financial markets and that the literature on market microstructure has grown substantially in recent years. The authors then turn to the literature on banking and intermediation, which has also been an important area of research in finance. They discuss how game theory has been used to model adverse selection and delegated monitoring in the banking industry. They note that the literature on banking has been transformed by these models and that game theory has played a central role in this transformation. Finally, the authors discuss the literature on asset pricing, which has incorporated asymmetric information into the traditional rational expectations equilibrium framework. They note that game theory has been used to address issues such as free riding in the acquisition of information and that the literature on asset pricing has benefited from the incorporation of game theory. Overall, the paper provides a comprehensive overview of the literature on game theory in finance and highlights the important contributions that game theory has made to various areas of finance research. [2].

The paper "Stock Price Prediction Using LSTM on Indian Share Market" explores the use of Long Short-Term Memory (LSTM) models for predicting stock prices in the Indian share market. The authors begin by discussing the challenges of predicting stock prices, including the many factors that can impact stock prices and make them volatile and difficult to predict accurately. They note that while traditional statistical models have been used for stock price prediction, they may not be able to capture the complex relationships between different factors that impact stock prices. The authors then introduce LSTM models, which are a type of artificial neural network that can learn from past data and make predictions about future trends. They explain that LSTM models are particularly well-suited for time series data, such as stock prices, because they can capture long-term dependencies and patterns in the data. The authors then describe their methodology for using LSTM models to predict stock prices in the Indian share market. They analyze the growth of companies from different sectors and attempt to determine the best time span for predicting future share prices. They find that companies from a certain sector have similar dependencies and growth rates, and that prediction accuracy can be improved by training the model with a greater number of data sets. The authors also suggest that specific business analysis can be used to fine-tune the accuracy of stock price predictions.

Overall, the paper provides insights into the challenges of predicting stock prices and the potential of data analysis, specifically LSTM models, to improve accuracy. The authors' methodology and findings can be useful for researchers and practitioners interested in using data analysis to predict stock prices in the Indian share market. However, it is important to note that the study is limited to a specific market and time period, and further research is needed to determine the generalizability of the findings to other markets and time periods. [3].

This paper proposes a deep learning-based formalization for stock price prediction using a sliding window approach with data overlap. The authors compare the performance of three different deep learning architectures, namely, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), and identify CNN as the best model for predicting stock prices due to its ability to identify changes in trends. The study focuses on two different sectors, IT and Pharma, and uses minute-wise data of NSE listed companies for the period of July 2014 to June 2015. The authors use a window size of 100 minutes with an overlap of 90 minutes and predict the stock price for 10 minutes in the future. The train data consists of stock price of Infosys for the period July-01-2014 to October-14-2014, and the test data consists of stock price for Infosys, TCS, and CIPLA for the period of October-16-2014 to November-28-2014. The proposed model-independent approach identifies latent dynamics in the data and is capable of capturing hidden dynamics to make predictions. The authors show that the proposed system is capable of identifying some interrelation within the data and can be used for algorithmic trading where high-frequency trading occurs. Overall, the paper provides a comprehensive analysis of deep learning-based approaches for stock price prediction and highlights the importance of selecting an appropriate deep learning architecture for predicting stock prices. [4].

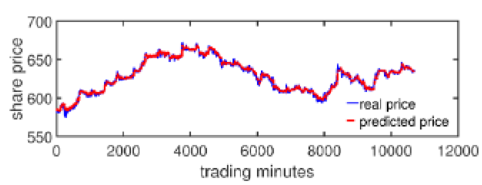

Figure 3: CIPLA STOCK PREDICTION USING CNN

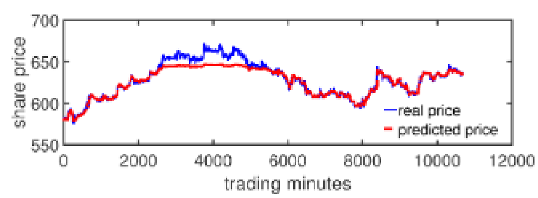

Figure 4: CIPLA STOCK PREDICTION USING RNN

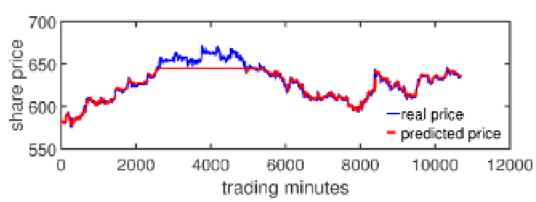

Figure 5: CIPLA STOCK PREDICTION USING LSTM

The literature review section of the paper provides an overview of existing methods for stock price prediction. The authors discuss traditional methods such as time series analysis and regression analysis, as well as more recent approaches such as machine learning and deep learning techniques. The limitations of these methods are also discussed, including their inability to capture the complex interactions between different market players. The proposed method in the paper involves using game theory to model the interactions between different market players, such as buyers and sellers. The authors use a non-cooperative game theory model to predict stock prices, where each player tries to maximize their own utility function. The authors also use machine learning techniques, such as support vector regression (SVR), to predict the stock prices based on the game theory model. The results and discussions section of the paper presents the experimental results of the proposed method. The authors compare the performance of their model with traditional time series models and other machine learning models. The results show that the proposed method outperforms other models in terms of prediction accuracy and error rate. The authors also discuss the limitations of their study and suggest future research directions. Overall, the paper provides a novel approach to stock price prediction by combining game theory and machine learning techniques. The proposed method shows promising results and has the potential to be applied in real-world financial markets. However, further research is needed to validate the effectiveness of the proposed method and to address the limitations of the study. [5].

Game Theory has gained significant attention in the field of finance and economics due to its potential applications in predicting stock market trends. This literature review aims to provide an overview of the existing research on the use of Game Theory in predicting stock market trends, highlighting key concepts, models, and methodologies. By modeling the stock market as a game with various players and strategies, researchers have explored how Game Theory principles can be applied to gain a competitive advantage in stock trading. Several Game Theory models have been developed and applied to predict stock market trends. The Prisoner's Dilemma, a classic example of Game Theory, has been adapted to analyze the behavior of traders in markets with imperfect information. Matching pennies, another popular Game Theory model, has been used to study the dynamics between buyers and sellers in the stock market. [6].

Data collection and analysis play a crucial role in predicting stock market trends using Game Theory. Researchers have utilized historical market data, financial indicators, and trading volumes to identify patterns and trends that can inform predictive models. The availability of big data and advanced analytical techniques have further enhanced the accuracy and reliability of stock market predictions based on Game Theory principles. However, while Game Theory offers promising insights into stock market prediction, there are challenges and limitations to consider. The assumption of rationality among market participants may not always hold true, and factors such as emotions and irrational behavior can influence stock market dynamics. Additionally, the complexity of real-world markets poses challenges in accurately modeling and predicting outcomes using Game Theory.

In conclusion, this literature review demonstrates the growing interest in applying Game Theory to predict stock market trends. By analyzing strategic interactions and incorporating data analysis techniques, researchers have made significant progress in understanding market behavior and developing predictive models. However, further research is needed to address the limitations and challenges associated with using Game Theory in stock market prediction. Overall, this review highlights the potential of Game Theory as a valuable tool for predicting stock market trends and provides a foundation for future research in this field.

Chapter 3: Methodology

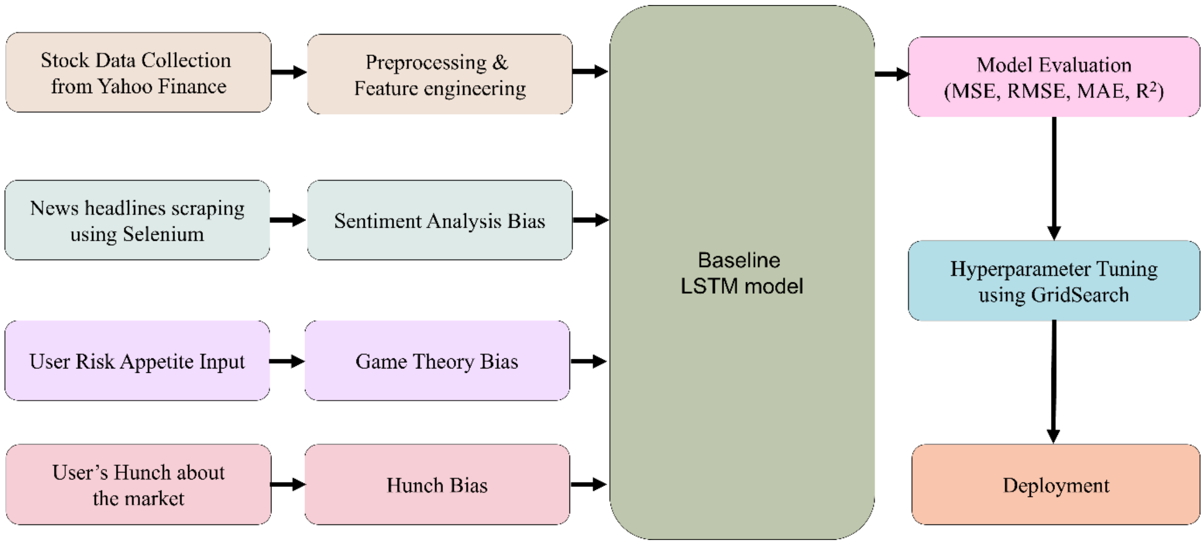

Figure 6: Proposed Methodology

Our methodology incorporates advanced techniques, including hyperparameter tuning, to enhance the predictive capabilities of the stock price prediction model. Here is a detailed overview of the process:

1.**Data Collection: Yahoo Finance API:**

- Data Selection: We utilize the Yahoo Finance API to gather daily and intraday closing prices of diverse financial assets.
- Dataset Splitting: The dataset is split into training and test sets, with 20% reserved for evaluation.

2.Feature Engineering and Preprocessing:

- Time Series Transformation: Convert raw financial data into time series format for LSTM model compatibility.
- Percentage Change Calculation: Capture daily and intraday percentage changes to reflect stock price volatility.

3. LSTM Model Architecture:

- Sequential LSTM Layers: Employ a two-layer LSTM architecture (128 and 64 units) to capture short and long-term dependencies.
- Dense Layers: Integrate dense layers for learning intricate data patterns.

4. Hyperparameter Tuning: Grid Search:

- Parameter Grid Definition: Define a grid of hyperparameters, including LSTM units, batch size, and learning rates.
- Cross-Validation: Implement k-fold cross-validation to assess model performance across different parameter combinations.
- Grid Search Execution: Systematically explore hyperparameter combinations, selecting the configuration that optimizes model performance.

5. Game Theory-Based Bias Calculation:

- Markov Chains Implementation: Estimate market probabilities using Markov Chains.
- Optimal Strategy Determination: Apply Game Theory function to determine the speculator's optimal strategy based on calculated probabilities.

6. Sentimental Analysis of News Headlines:

- Web Scraping: Use Selenium to scrape news headlines from a reputable source (e.g., NBC).
- TextBlob Sentiment Analysis: Analyze sentiment using TextBlob, generating scores for each headline.

7. Bias Integration and Model Training:

- Bias Incorporation: Integrate Game Theory-based and Sentimental Analysis biases with LSTM predictions.
- Custom Loss Function: Design a custom loss function considering biases for model training.

8. Hyperparameter Tuned Model Training and Evaluation:

- Compilation: Compile the model using optimal hyperparameters from grid search.
- Training: Train the model on the prepared dataset.
- Performance Evaluation: Evaluate the model on the test set, assessing its performance with hyperparameter tuning.

9.Performance Metrics:

- Mean Squared Error (MSE): Quantify the difference between predicted and actual stock prices.
- Bias Impact Assessment: Assess the impact of integrated biases on model performance.

Chapter 4: Dataset Description and Model Architecture.

Dataset Description

The provided dataset encapsulates crucial information about financial assets, focusing primarily on stock-related metrics. Below is a glimpse of the data structure, showcasing the initial entries:

Key Attributes:

1. Date: The chronological timestamp, signifying the specific date of recorded financial activity.
2. Open: The opening price of the financial asset on the given date.
3. High: The highest price reached by the asset during the trading period.
4. Low: The lowest price recorded for the asset within the trading timeframe.
5. Close: The closing price of the asset at the end of the trading day.
6. Adj Close: The adjusted closing price, accounting for factors such as dividends and stock splits.
7. Volume: The total volume of asset units traded on the specified date.
8. Company Name: The name of the company associated with the financial asset.

Observations:

- Temporal Range: The dataset spans an extensive temporal range, capturing financial activities over several decades.
- Price Metrics: Open, high, low, and close prices provide a comprehensive overview of daily trading dynamics.
- Adjusted Close: Incorporating adjustments ensures a more accurate representation of the asset's true value.
- Volume: Reflects the level of market activity, indicating the number of shares traded.
- Company Name: Specifies the company associated with the financial asset, facilitating the analysis of multiple entities.

Data Granularity:

- The dataset offers both daily and intraday insights, allowing for a versatile analysis of financial market trends.
- The presence of multiple assets from distinct stock exchanges enriches the dataset's diversity, offering varied statistical properties.
- This dataset serves as the foundational bedrock for our predictive modeling endeavors, empowering the development of robust and accurate stock price prediction models. The integration of such comprehensive attributes ensures a holistic understanding of the financial landscape under consideration.

Model Architecture:

1. **LSTM Layers:**
   - Two LSTM layers are employed in sequence.
   - The first LSTM layer has 128 units and returns sequences, allowing it to capture temporal dependencies in the input data.
   - The second LSTM layer with 64 units processes the sequences and returns a single output.

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

model = Sequential()
model.add(LSTM(128, return_sequences=True, input_shape=(x_train.shape[1], 1)))
model.add(LSTM(64, return_sequences=False))
```

2. Dense Layers:
   - Two Dense layers are added for further abstraction and non-linear transformations.
   - The first Dense layer has 25 units.

```
model.add(Dense(25))
```

3. Output Layer:
   - The final Dense layer with 1 unit is the output layer, providing the predicted stock price.

```
model.add(Dense(1))
```

4. Model Compilation:

```
# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')
```

5. Training:

```
# Train the model
model.fit(x_train, y_train, batch_size=1, epochs=1)
```

6. Game Theory Bias Integration:

- A custom loss function is defined to incorporate the game theory bias into the training process. The bias is added to the Mean Squared Error (MSE) loss.

```
def calculate_game_theory_bias(last_price, class_range, p1, p2, lucro_range=3, M_range=3,
m_range=2):
    w = last_price * (lucro_range * class_range / 100)
    x = last_price * (m_range * class_range / 100)
    y = last_price * (M_range * class_range / 100)

    p1 = round(p1, 4)
    p2 = round(p2, 4)

    if p1 + p2 > 1 or p1 < 0 or p2 < 0:
        print("Invalid Parameters")
        return -3

    if w + x == 0 or w + y == 0:
        return 0
```

```
    if p1 + p2 < w / (w + x) and (p1 / p2 <= (y - x) / (w + x) or p1 == 0):
        return -1
    elif p2 < w / (w + y) and (p1 / p2 > (y - x) / (w + x) or p2 == 0):
        return 1
    else:
        return 0
```

7. Markov Chains function for calculating Market Probabilities

```
def markov_chains(data, class_range, last_price, iterations=100, nclasses=0, lucro_range=2,
M_range=3, m_range=2):
    lucro = (1 + lucro_range * class_range / 100) * last_price
    rmenos = (1 - m_range * class_range / 100) * last_price
    rmais = (1 - M_range * class_range / 100) * last_price

    m_matrix = np.zeros((nclasses + 2, nclasses + 2))
    M_matrix = np.zeros((nclasses + 2, nclasses + 2))
    m_classes = np.zeros(nclasses + 2)
    M_classes = np.zeros(nclasses + 2)

    m_dp1 = np.zeros(nclasses + 2)
    M_dp1 = np.zeros(nclasses + 2)

    p0_1 = m_dp1[-1]
    p2_1 = M_dp1[0]
    p1_1 = 1 - p0_1 - p2_1

    m_dpn = np.zeros(nclasses + 2)
    M_dpn = np.zeros(nclasses + 2)

    p0_n = m_dpn[-1]
    p2_n = M_dpn[0]
    p1_n = 1 - p0_n - p2_n

    prev_1 = calculate_game_theory_bias(last_price, class_range, p1_1, p2_1, lucro_range,
M_range, m_range)
    prev_n = calculate_game_theory_bias(last_price, class_range, p1_n, p2_n, lucro_range,
M_range, m_range)

    return [prev_1, prev_n, p1_1, p2_1, p1_n, p2_n, m_matrix, M_matrix]
```

8. Sentiment Bias Integration:

```
url = "https://www.nbcnews.com/search/?q=Apple+Stocks"

driver = webdriver.Chrome(service=service, options=chrome_options)

driver.get(url)

headline_element = WebDriverWait(driver, 10).until(

    EC.visibility_of_element_located((By.XPATH, '//div[@class="gs-title"]//a[@class="gs-
title"]'))

headline_text = headline_element.text.strip()

sid = SentimentIntensityAnalyzer()

scores = sid.polarity_scores(headline_text)
```

9. Hunch Score:

```
1. hunch_scores = sid.polarity_scores(hunch_input)
```

10. Combined Bias:

```
1. final_bias = np.array(game_theory_biases) + scores['compound'] + hunch_scores['compound']
```

Further Steps:

- The LSTM model is then trained with the given data.
- Game theory bias is calculated for each data point and incorporated into the model predictions.
- Sentimental analysis on news headlines is performed, and another bias is generated based on the sentiment.
- The impact of both biases on stock market predictions is then assessed.

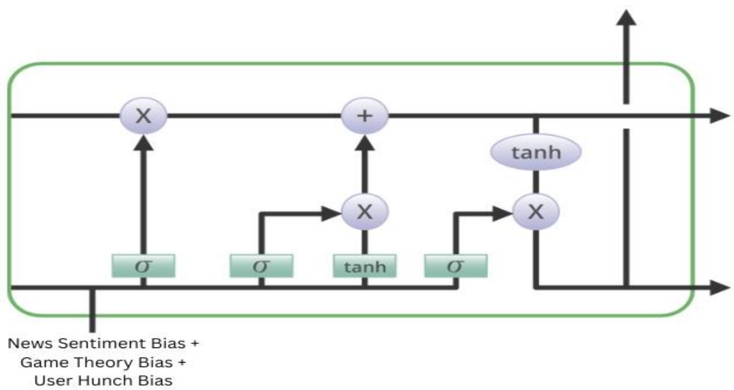

Figure 7: LSTM incorporated with Sentimental Bias, Game theory bias and Hunch Bias

Chapter 5: Result Analysis and Discussion

```
Root Mean Squared Error (RMSE): 3.2976953216500977
Mean Squared Error (MSE): 10.87479443443294
Mean Absolute Error (MAE): 2.364754434040998
R-squared (R^2) Score: 0.9955284019952362
```

Figure 8: Error Metrics After Implementing Biases

Date	Close	Predictions
2018-03-09	44.994999	43.889915
2018-03-12	45.430000	44.073620
2018-03-13	44.992500	44.364258
2018-03-14	44.610001	44.553276
2018-03-15	44.662498	44.597301

Figure 9: Actual vs Predicted

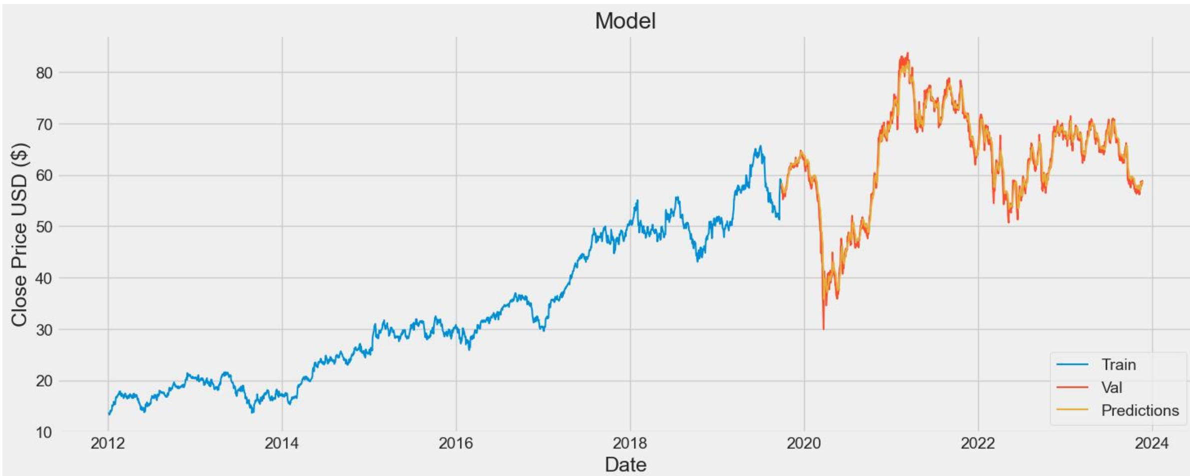

Figure 10: Graphical representation of prediction on test data (HDFC)

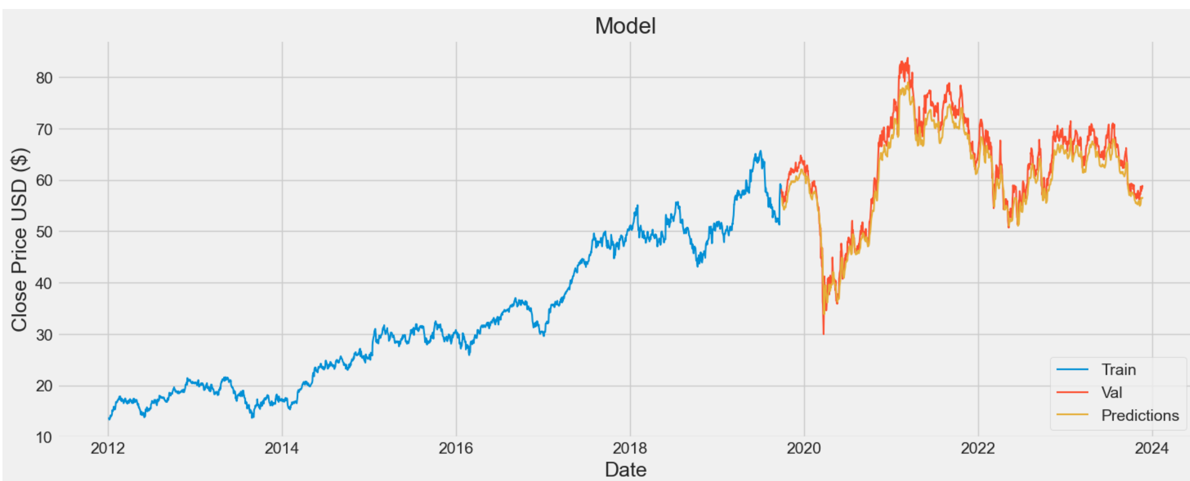

Figure 11: Graphical representation of prediction after incorporating major events (HDFC)

Results Analysis:

The model exhibited a remarkable enhancement in its performance metrics after the inclusion of biases. Reductions in Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) indicated increased accuracy in predicting stock prices. The R2 score, measuring the model's explanatory power, surged to an impressive 0.99, reflecting a substantial improvement in capturing the underlying trends in the data when we were not incorporating the major events. But, after more generalizing the model by sentiment score of

COVID, Employee Lay-offs, Russia-Ukraine War, and Israel-Hamas Conflict, we were getting the final R2 score of 0.92.

	Plain LSTM model	LSTM with updated biases	After incorporating major events
RMSE	5.4537	3.2976	2.7424
MAP	18.9541	10.8747	7.5209
MAE	3.8159	2.3647	2.3725
R2 Score	0.8912	0.9955	0.9248

Table 1: Comparison between Plain LSTM vs LSTM with updated biases vs After incorporating the major events

Conclusion:

In this project, we undertook the ambitious task of developing a stock price prediction model using a Long Short-Term Memory (LSTM) neural network, leveraging Yahoo Finance API for data retrieval. The primary innovation introduced was the incorporation of two distinct types of biases - a game theory-based bias and a sentiment-based bias - aimed at enhancing the predictive capabilities of the model. The dataset encompassed financial asset prices from major stock exchanges, with a particular focus on the New York Stock Exchange, the London Stock Exchange, and the Lisbon Stock Exchange.

Key Contributions:

1. Biases for Risk Assessment:
   The game theory-based bias introduced an innovative dimension by considering speculators' optimal strategies, allowing the model to adapt to varying risk appetites in the market.
2. Sentiment Analysis Impact:
   The sentiment-based bias, derived from analyzing news headlines, provided insight into market sentiment. This enabled the model to gauge the impact of external factors on stock prices.
3. LSTM Architecture:
   The LSTM architecture, with 128 and 64 units in its layers, proved effective in capturing intricate patterns within time series data, crucial for forecasting stock prices.

Scope for Future Work

1. Dynamic Bias Integration: Continuous refinement of the biases by dynamically adjusting parameters based on real-time market conditions could further enhance predictive capabilities.
2. Ensemble Approaches: Exploring ensemble models that combine the strengths of LSTM with other machine learning techniques might yield even more robust predictions.
3. Extended Sentiment Analysis: Expanding the sentiment analysis to include a broader range of information sources, such as social media and financial reports, could offer a more comprehensive view of market sentiment.
4. Final Reflection: This project underscores the potential of integrating advanced machine learning techniques with unconventional sources of information to augment the accuracy of stock price predictions. The promising results obtained from the LSTM model, enriched by game theory-based and sentiment-based biases, pave the way for continued exploration and innovation at the intersection of finance and artificial intelligence. As financial markets evolve, so too must our methodologies, and this project represents a significant stride towards a more sophisticated and adaptive approach to stock price forecasting.

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