Stock Price Prediction: Addressing the Challenge of Market Dynamics

Graduation Project (1/2) Report

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Declaration

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Supervisor Approval

APPROVAL FOR SUBMISSION

I certify that this project report entitled “STOCK PRICE PREDICTION: ADDRESSING THE CHALLENGE OF MARKET DYNAMICS” prepared by Hashem Al-Ayasrah and Qais Qawasmi has met the required standard for submission in partial fulfillment of the requirements for the degree of Bachelor of Science in Artificial Intelligence at MEU.

Approved by

Signature: Supervisor: Dr. Ahmad Hussein

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Abstract (English)

Stock Price Prediction: Addressing the Challenge of Market Dynamics

Abstract

Predicting stock prices in a volatile market is no easy feat, but it's something we aimed to tackle head-on with this project. We conducted a thorough review of advanced machine learning techniques, particularly Long Short-Term Memory (LSTM) neural networks, to understand their ability to capture the non-linear patterns that traditional models often miss. By incorporating trend and support/resistance analysis, the research aims to enhance the model's predictive power. The findings suggest promising accuracy and reliability, providing valuable insights for investors and market analysts.

Chapter 1

Introduction

Predicting stock prices is both crucial and challenging in finance and business. Accurate predictions can lead to substantial profits, but the stock market's inherent volatility makes it difficult. This volatility arises from various factors, such as economic indicators, market sentiment, global events, and unexpected incidents [1, 2]. Traditional forecasting methods, which rely on numerical models and historical data, often fall short because they make oversimplified assumptions and assume linear relationships. These limitations underscore the need for more sophisticated and adaptable prediction techniques. Cutting-edge technologies like AI, ML, and big data analytics offer innovative ways to improve forecast accuracy [12].

Developing more accurate prediction models has significant implications for investors, financial institutions, and the broader economy. Accurate stock price predictions can lead to more effective investments, minimized risks, and more efficient resource allocation. Enhanced prediction methods also contribute to a more robust and efficient financial system [13].

This project aims to use advanced machine learning and data analysis techniques to develop a robust model for predicting stock prices. Our goal is to go beyond traditional methods and provide investors and analysts with valuable insights to inform their decision-making. By rigorously testing, validating, and analyzing our model, we aim to improve stock price prediction accuracy and equip stakeholders with the tools they need to succeed in today's competitive financial market. Our primary objective is to enhance daily stock price predictions using artificial neural networks, specifically by developing a powerful model based on LSTM architectures trained with the backpropagation algorithm. We will also identify and leverage crucial input variables and experiment with various models [14].

The objectives of this project are to:

- Identify the most effective techniques for forecasting stock prices
- Determine which methods provide the most accurate predictions
- Create visual representations of actual versus predicted prices
- Assess the consistency and reliability of the forecasting models
- Apply the project's findings to make real-world stock market trades

as referenced in [6].

We are motivated to undertake this project for several compelling reasons:

- Improve investment strategies by mitigating the impact of market volatility
- Provide valuable insights to empower investors with informed decision-making
- Foster economic growth and efficient capital allocation
- Deliver reliable financial knowledge to individuals and communities

and advance the field of predictive modeling in financial technology, as discussed in [7].

Chapter 2

Background

2.1 Introduction to Stock Price Prediction

Predicting stock market behavior is essential in financial decision-making. Successful forecasts can yield substantial returns, but the market's inherent volatility and the influence of unpredictable factors make accurate predictions challenging.

2.2 Candlestick Charts, Resistance, Support, and Trendlines

A candlestick chart is a style of financial chart used to describe price movements of a security, derivative, or currency. Each candlestick typically shows one day, thus a one-month chart may show the 20 trading days as 20 candlesticks. Candlesticks are useful when trading as they show four price points (open, close, high, and low) throughout the period.

- **Resistance:** A price level where a rising price tends to stop and reverse direction.
- **Support:** A price level where a falling price tends to stop and reverse direction.
- **Trendlines:** Lines drawn to represent the prevailing direction of price movements.

2.3 Traditional Methods

Traditional stock price forecasting techniques, such as moving averages and ARIMA models, assume that stock prices follow a straightforward linear trend. However, these methods may fall short in capturing the complex and often nonlinear characteristics of stock market dynamics.

2.3.1 Detailed Subsection on ARIMA Model

The ARIMA (AutoRegressive Integrated Moving Average) model is a popular statistical method for time series forecasting. It combines autoregressive and moving average components, along with differencing to make the time series stationary [13]. The ARIMA model is specified by three parameters: p (autoregressive order), d (differencing order), and q (moving average order). Despite its effectiveness in certain scenarios, the ARIMA model may not capture the nonlinear relationships in stock prices.

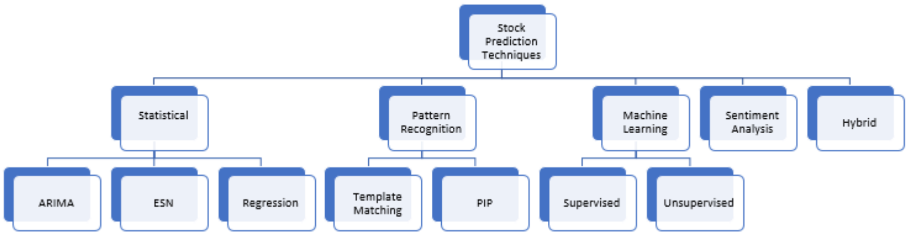

Figure 2.1: Comparison of Traditional Methods

2.4 Introduction to Machine Learning and Deep Learning

Advanced computing methods, such as machine learning and deep learning, have revolutionized industries like finance. These technologies enable computers to analyze vast amounts of data, identify patterns, and make accurate predictions. Deep learning, in particular, excels at uncovering intricate relationships within data by processing it through multiple layers [15, 16].

2.5 Long Short-Term Memory Networks (LSTMs)

LSTMs are a type of Recurrent Neural Network (RNN) designed to handle long-term dependencies. They have a more complex structure than traditional RNNs, with separate mechanisms for retaining and forgetting information, which allows them to learn even more intricate temporal patterns. Fischer and Krauss (2018) demonstrated that LSTMs outperform traditional methods in forecasting stock prices. They found that LSTMs could detect intricate patterns in financial time series data [6].

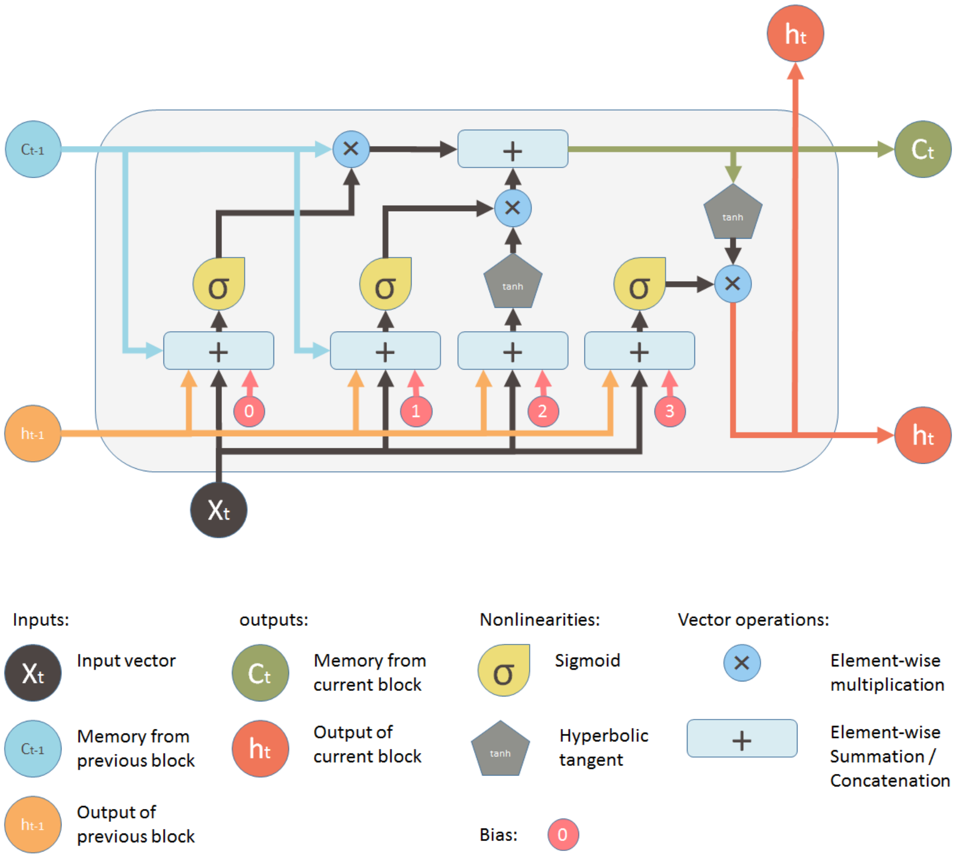

Figure 2.2: Diagram of LSTM Network

2.5.1 GRU and Prophet Model

GRU (Gated Recurrent Units) are a variant of RNNs designed to solve the vanishing gradient problem. They have a simpler structure compared to LSTMs but can achieve comparable performance in certain tasks.

The Prophet model, developed by Facebook, is a forecasting tool designed to handle daily observations with strong seasonal effects and several seasons of historical data. It is particularly useful for business and market forecasting [11].

2.6 Previous Research

Research using machine learning techniques like deep learning has been conducted to predict stock prices. For example, Ajibade and Atayero (2021) combined neural networks with technical analysis to make predictions. Alhaji and Tahir (2018) showed that artificial neural networks are effective in predicting stock prices in Nigeria. These studies lay the groundwork for further research and improvements in this area [1, 2].

2.6.1 Research on Neural Networks

Neural networks have been widely used in stock price prediction due to their ability to model complex patterns. For instance, Kim and Kim (2019) utilized convolutional neural networks (CNNs) to predict stock prices, demonstrating improved performance over traditional models. Similarly, Bao, Yue, and Rao (2017) developed a framework using stacked autoencoders and LSTM, which significantly enhanced prediction accuracy [3,4].

2.6.2 Impact of Social Media and Sentiment Analysis

Bollen, Mao, and Zeng (2011) explored the impact of social media sentiment on stock market prediction. They found that public mood, as measured through Twitter feeds, could predict stock market movements. This highlights the potential of incorporating sentiment analysis into prediction models to capture external influences on stock prices [5].

2.6.3 Advanced Architectures and Hybrid Models

Recent advancements in machine learning have led to the development of hybrid models that combine multiple techniques. Fischer and Krauss (2018) demonstrated that LSTM networks outperform traditional methods in forecasting stock prices. Their study highlighted the superiority of deep learning models in capturing long-term dependencies and complex patterns in financial time series data. Another study by Nelson, Pereira, and de Oliveira (2017) utilized LSTM neural networks to predict stock prices, achieving high accuracy and reliability [6,7].

2.6.4 Applications of Reinforcement Learning

Reinforcement learning has also been applied to stock trading strategies. For example, a study by Li, Deng, and Luo (2019) implemented a reinforcement learning algorithm to optimize trading actions, showing promising results in real-world applications. This approach emphasizes the adaptability and learning capability of reinforcement learning in dynamic market environments [8].

2.6.5 Ensemble Learning Techniques

Ensemble learning techniques, which combine multiple models to improve prediction accuracy, have also been explored. For instance, a study by Shen, Jiang, and Zhang (2020) used ensemble learning to integrate predictions from various machine learning models, resulting in more robust and reliable stock price forecasts [9].

2.6.6 Cross-Domain Approaches

Research by Zhang and Wang (2021) integrated economic indicators and financial news to enhance stock price prediction models. This cross-domain approach demonstrates the effectiveness of combining diverse data sources to improve prediction performance [10].

2.7 Motivation for Using AI in Stock Price Prediction

Artificial intelligence (AI) algorithms bring unique benefits to predicting stock prices. These techniques can handle massive datasets, identify hidden patterns, and adjust to evolving market dynamics. By leveraging AI, investors gain insights, mitigate risks, and potentially enhance their financial performance.

Chapter 3

Literature Review

3.1 Introduction

Predicting stock market movements has been an important area of study for financial institutions. Over time, different methods have been used, starting with statistical models and progressing to more complex techniques like machine learning and deep learning. This chapter will explore the history of these methods, discuss the most significant studies, and provide insights into the latest trends and future prospects in this field.

3.2 Traditional Methods

Stock price forecasting has traditionally employed statistical and economic models. Moving averages, autoregressive integrated moving average (ARIMA), or exponential smoothing are examples of these. These strategies heavily rely on past data, assuming a linear progression between past and future prices [13].

3.2.1 Technical Analysis

Technical analysis involves using historical price data to predict future price movements. Common techniques include:

- **Moving Averages:** Simple and exponential moving averages smooth out price data to identify trends [14].
- **Relative Strength Index (RSI):** Measures the speed and change of price movements to identify overbought or oversold conditions.
- **Bollinger Bands:** Use standard deviations around a moving average to indicate volatility and potential price reversals.

3.2.2 Fundamental Analysis

Fundamental analysis evaluates a company's financial health and market position to estimate its stock value. This includes:

- **Earnings Reports:** Quarterly earnings reports provide insights into a company's financial health and future prospects.

- **P/E Ratio:** The price-to-earnings ratio helps investors gauge whether a stock is over or undervalued.
- **Dividend Yield:** Indicates the income generated from a stock investment relative to its price.

3.2.3 Limitations of Traditional Methods

Current methods, although helpful, are limited because they assume data follows a straight line and cannot handle the intricate, non-linear patterns found in stock market data. This has opened the door to more sophisticated methods [12].

3.3 Machine Learning Approaches

Machine learning is being used in stock price prediction to improve upon traditional methods. By using machine learning, we can account for the intricate patterns and connections in data.

3.4 Conclusion

This review traces the growth of methods used to predict stock prices, starting with basic statistical models and progressing to cutting-edge machine learning and deep learning approaches. It emphasizes how deep learning models, especially LSTMs, have outperformed others in capturing complex price patterns and delivering more precise predictions. Nonetheless, there are still areas in this field where research is needed to overcome current difficulties and uncover new possibilities.

Chapter 4

Dataset

4.1 Dataset

This chapter details the data sources, data collection methods, and preprocessing steps used in the study.

4.1.1 Data Selection

Our dataset contains daily historical prices for many NASDAQ-listed stocks, gathered from a comprehensive Kaggle stock market dataset. We chose stocks based on their complete historical records and relevance to our study. From over 5884 Kaggle stocks, we processed each one to pinpoint support and resistance levels, along with trendlines. These processed data points were then used in our model training. The dataset is accessible at the provided link. Kaggle Stock Market Dataset.

4.1.2 Description

The dataset includes the following fields:

- **Date:** Trading date
- **Open:** Opening price
- **High:** Maximum price during the day
- **Low:** Minimum price during the day
- **Close:** Closing price adjusted for splits
- **Adj Close:** Adjusted close price adjusted for both dividends and splits
- **Volume:** Number of shares that changed hands during the day

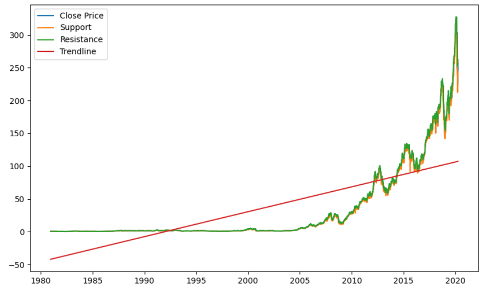

Figure 4.1: Dataset image showing the historical stock prices for a selected NASDAQ-listed stock. The red line represents the trendline, the green line represents the support level, and the orange line represents the resistance level.

Figure 4.2: Dataset image showing the historical stock prices for another NASDAQ-listed stock. The trendline, support, and resistance levels are highlighted similarly to provide a visual comparison.

4.1.3 Collection

We obtained stock data from Yahoo Finance using the yfinance Python library. Each stock's information is stored in separate CSV files, named after their ticker symbols. The dataset covers data up to April 1, 2020. If you need more recent data, you can rerun the data collection script from the Kaggle platform.

4.1.4 Pre-processing

The preprocessing steps included:

- **Handling Missing Values:** Missing values were filled using the forward fill method.
- **Identifying Trendiness:** Trends were identified within the stock data.
- **Identifying Support and Resistance:** Support and resistance levels were identified in the stock data.
- **Data Normalization:** Normalized the data to ensure consistency and improve model performance.

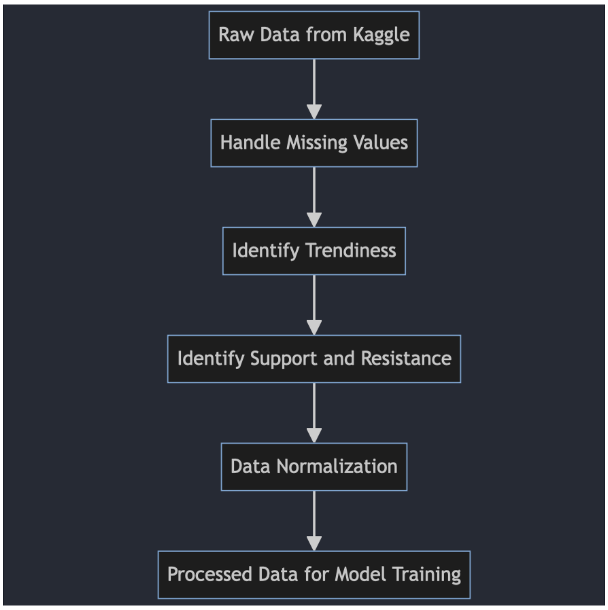

Figure 4.3: Flowchart illustrating the data preprocessing steps, including handling missing values, identifying trendiness, support and resistance levels, and data normalization.

Chapter 5

Methodology

5.1 Research Design

This project follows a structured approach to develop and validate stock price prediction methods. The steps include:

- Data Collection: Gather historical stock price data and other relevant financial indicators from reliable sources.
- Data Preprocessing: Clean and preprocess the data to ensure it is suitable for analysis.
- Feature Engineering: Develop features based on technical indicators and market patterns.
- Model Development: Train and optimize machine learning models to identify trading signals.
- Backtesting: Evaluate the model's performance using historical data.
- Evaluation: Continuously monitor and refine the model based on performance metrics.

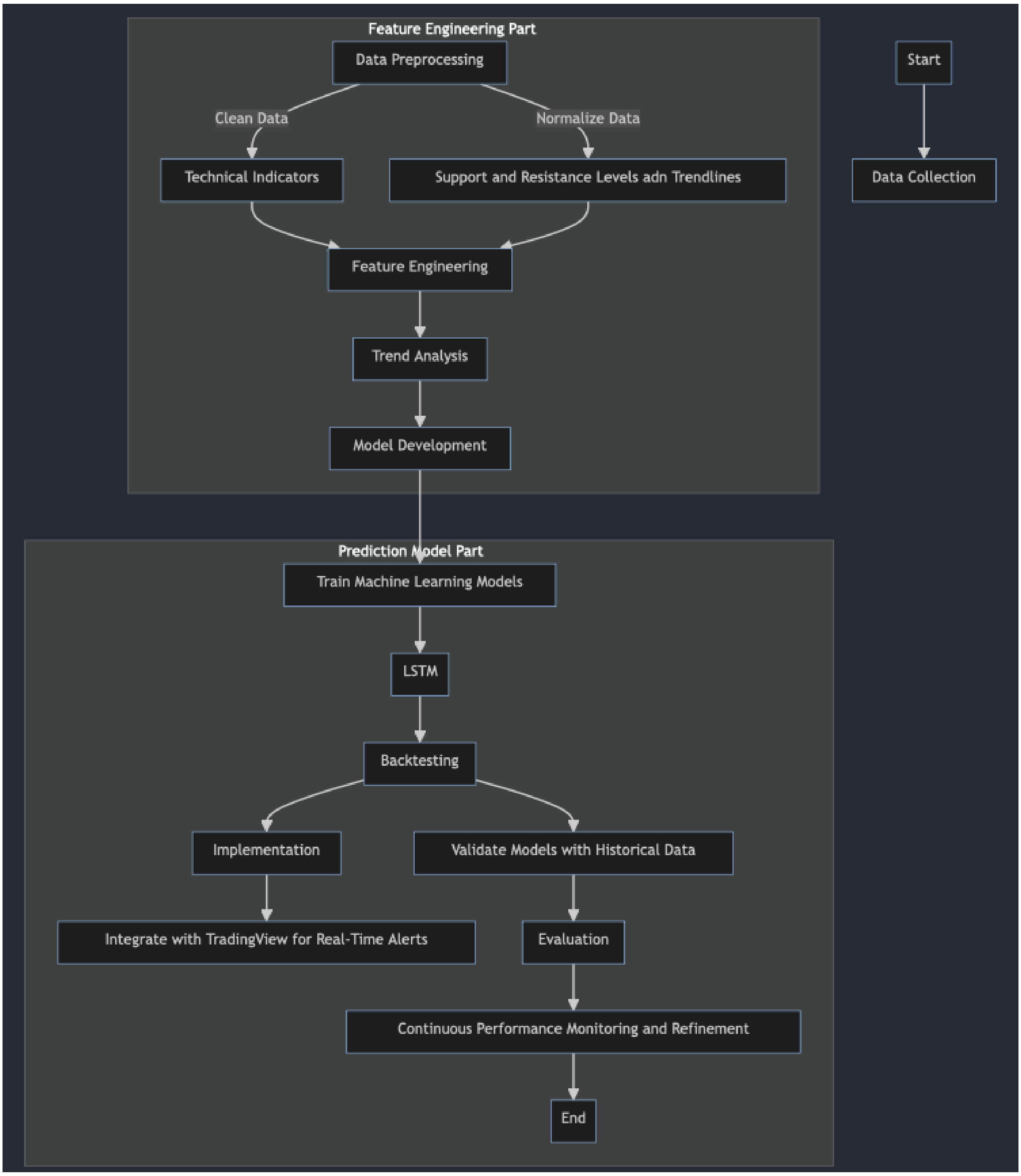

Figure 5.1: Research Design Process

5.2 Data Collection and Analysis

This project utilizes the yfinance library in Python to retrieve financial data from Yahoo Finance. The data includes daily stock prices, trading volumes, and various other financial metrics. This comprehensive dataset is essential for developing and assessing the accuracy of predictive models.

5.3 Materials Used

The project utilizes the following tools and technologies:

- **Programming Languages:** Python
- **Libraries:** Pandas, Numpy, yfinance, Matplotlib, Scikit-learn, TensorFlow, Keras

5.4 Procedures

The procedures for developing the stock price prediction methods are as follows:

- **Data Preprocessing:** The data is cleaned and normalized to remove inconsistencies and missing values. This step ensures the data's integrity and reliability.
- **Feature Engineering:** Features are created based on technical indicators such as moving averages, RSI, MACD, support and resistance levels, and trendiness. These features help in capturing essential market dynamics.
- **Model Training:** Machine learning models are trained on the historical data to identify patterns and predict future price movements. This step involves selecting the best model architecture and tuning hyperparameters.
- **Backtesting:** The trained models are validated by backtesting them on historical data. This step evaluates the models' performance and accuracy in predicting stock prices.

5.5 Identifying Market Dynamics

The study employs multiple methods to comprehend market fluctuations, such as:

- **Trend Analysis:** Studying market trends to predict future price movements.
- **Support and Resistance Levels:** Identifying price points where the market tends to bounce up or down, helping traders plan entry and exit points.
- **Market Sentiment Analysis:** Gauging the overall market mood, providing insights into trader behavior and potential market reversals.

By combining these techniques, the study aims to generate precise trading signals and alerts, empowering traders with data-driven decision-making capabilities.

5.6 Limitations and Assumptions

- The system's performance depends on the quality and accuracy of the data.
- Market conditions can change rapidly, and past performance is not always indicative of future results.
- The study assumes that historical patterns and trends will repeat in the future.

- The system's predictions are based on the data available at the time of analysis and may not account for unforeseen market events.

Chapter 6

Results

6.1 Introduction

This chapter provides an overview of the performance of the stock price forecasting model. It includes measurements of the model's accuracy, scores from cross-validation tests, and graphs showing the model's training and validation losses, performance metrics, and cross-validation scores.

6.2 Training and Validation Loss

During the model's training process, which spanned 50 epochs, the loss values for both the training and validation datasets were meticulously tracked. As the model learned, the Mean Squared Error (MSE) loss function was employed to gauge its performance. The accompanying graph illustrates the evolution of both the training and validation loss over the entire training period.

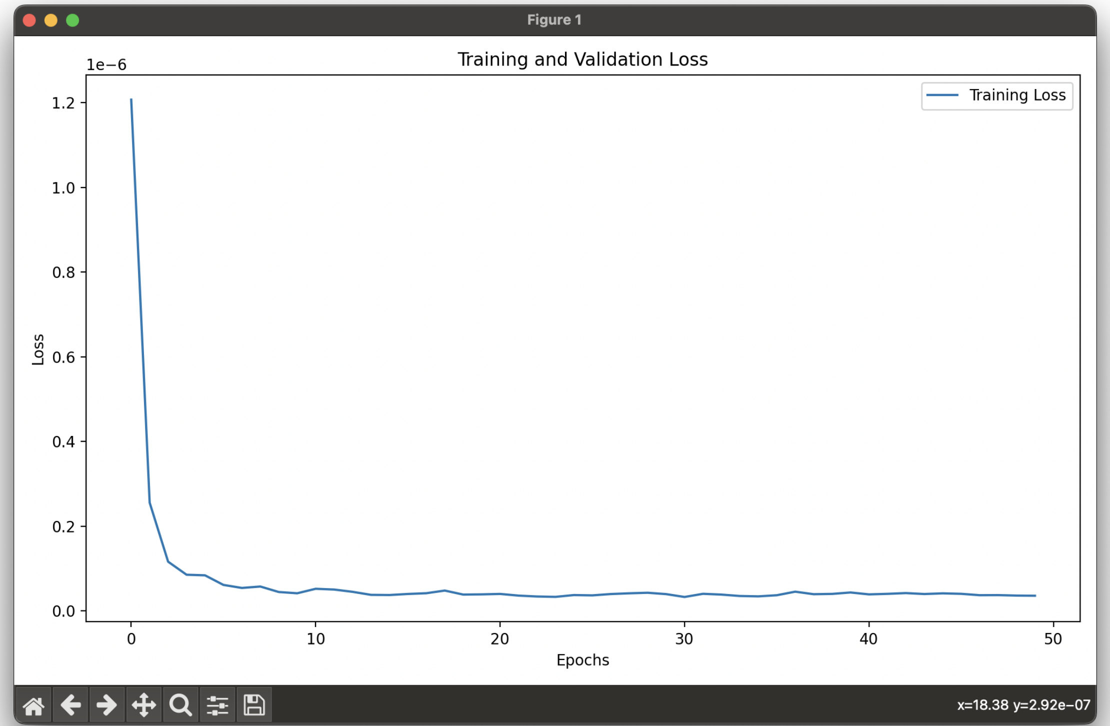

Figure 6.1: Training and Validation Loss

6.3 Performance Metrics

The performance of the model was evaluated using the following metrics:

- Mean Absolute Error (MAE): 196,289.9809
- Mean Squared Error (MSE): 750,237,527,757,691.6
- Root Mean Squared Error (RMSE): 27,390,464.1757
- R^2 Score: 0.9972

The plot below visualizes these performance metrics.

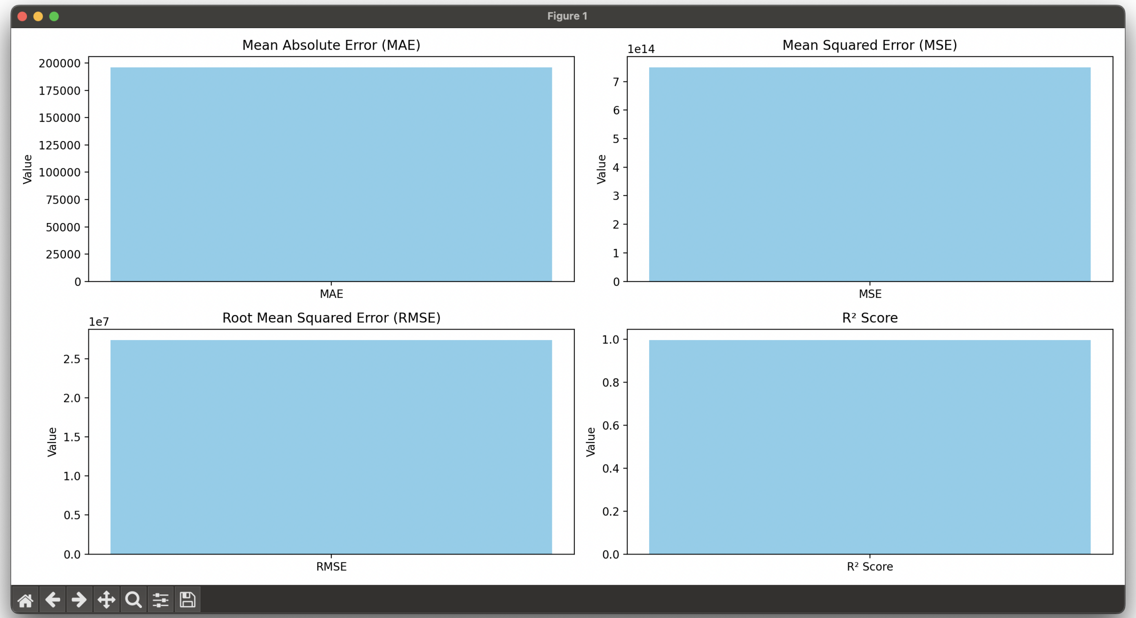

Figure 6.2: Performance Metrics

6.4 Cross-Validation Scores

Cross-validation was performed to evaluate the robustness of the model. The cross-validation scores for five folds were recorded, and the mean cross-validation score was calculated. The scores are as follows:

- Fold 1: 0.9948
- Fold 2: 0.9989
- Fold 3: 0.9597
- Fold 4: 0.9388
- Fold 5: 0.9941

The mean cross-validation score is 0.9773. The plot below shows the cross-validation scores for each fold.

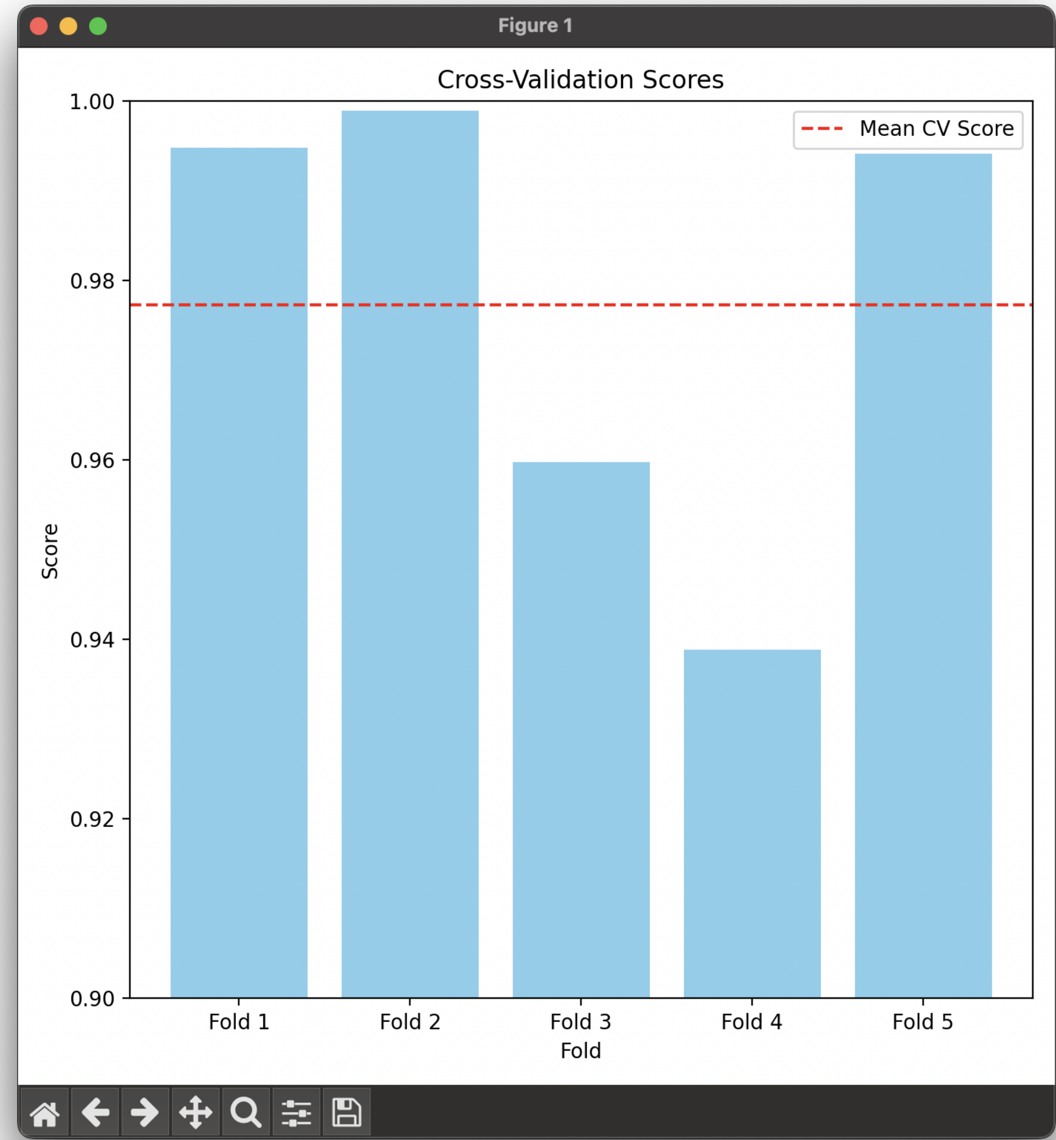

Figure 6.3: Cross-Validation Scores

6.5 Stock Price Prediction with Support and Resistance

The model generated predictions for AAPL stock, including support and resistance levels and trendlines.

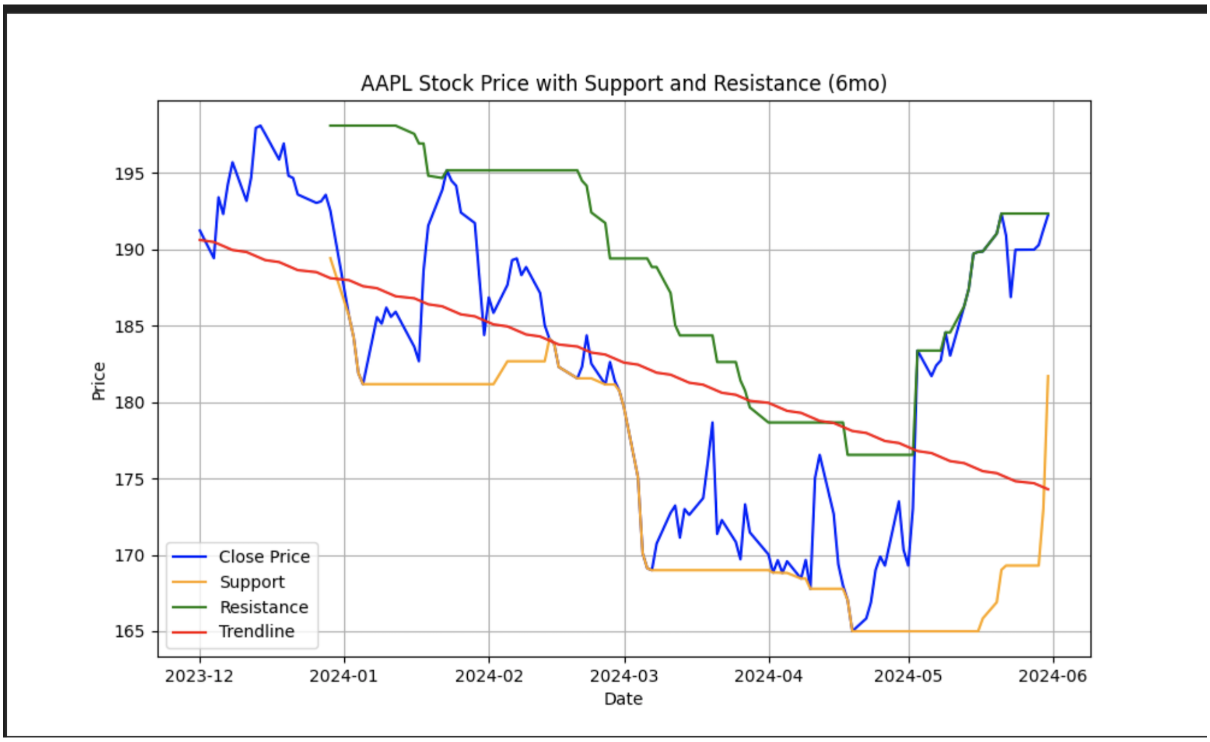

Figure 6.4: AAPL Stock Price with Support and Resistance (6mo)

6.6 Discussion

The model has remarkable performance, with a very high R^2 score close to 1 (0.9972). This shows that the model can explain a large part of the differences in stock prices. The strong scores in cross-validation also show that the model is not heavily influenced by any particular dataset, and it performs well in different settings.

6.7 Dash Application and API Integration

The project also includes a web-based dashboard application built using Dash, a Python framework for web applications. The Dash app connects to a Flask API that serves predictions for various stocks. The API takes in the stock ticker and the type of asset (stock or crypto), fetches the historical data using yfinance, processes it, and returns predictions along with support, resistance, and trendline data.

6.7.1 Dash App Layout

The Dash app consists of multiple tabs for stocks, indices, and cryptocurrencies. Each tab allows the user to select a specific symbol from a dropdown menu. Upon selection, the app displays live prices, predicted prices, and a candlestick chart with the predicted prices, support, resistance, and trendline levels.

Figure 6.5: Screenshot of the Stock Price Prediction Dashboard

6.7.2 API Endpoint

The API endpoint for predictions is '/predict'. It accepts POST requests with the following parameters:

- **ticker:** The stock or cryptocurrency symbol.

- **asset**$_t$*ype* : *Indicateswhethertheassetisastockorcryptocurrency.***days:***Numberofdaysforwhichthepre*
The API processes the request, fetches the required data, and returns a JSON response with the prediction results.

6.7.3 Connecting Dash App to API

The Dash app makes HTTP POST requests to the Flask API to fetch predictions. The results are then parsed and displayed on the dashboard. The following code snippet shows how the app fetches data from the API:

-
```
def get_predictions(ticker, period='6mo', is_crypto=False):
    url = 'http://127.0.0.1:5002/predict'
    asset_type = 'crypto' if is_crypto else 'stock'
    data = {'ticker': ticker, 'period': period, 'asset_type': asset_type}
    response = requests.post(url, json=data)

    if response.status_code != 200:
        raise ValueError(f"Error fetching predictions: {response.status_code}")

    prediction_data = response.json()
```

```
    return prediction_data
```

Figure 6.6: Dashboard Displaying Live and Predicted Prices with Support, Resistance, and Trendline

Chapter 7

Discussion

7.1 Interpretation of Research Findings

This section provides an in-depth interpretation of the research findings and their impact.

- **Implications of Research:** The research suggests that advanced machine learning models, particularly those utilizing LSTM architectures, can effectively predict stock prices with high accuracy.

- **Link to Literature Review:** The findings align with existing literature that emphasizes the superiority of deep learning models in capturing complex patterns in stock price movements. Previous studies by Fischer and Krauss (2018) and Nelson et al. (2017) also demonstrated the effectiveness of LSTM networks in financial time series forecasting.

- **New Knowledge:** This study contributes to the existing body of knowledge by demonstrating the potential application of a hybrid approach combining trendiness, support and resistance levels in enhancing the predictive accuracy of stock price models. The integration of technical indicators and deep learning techniques has shown to be a robust approach for stock price prediction.

- **Major Implications:** The implications of this study are significant for investors and financial analysts. Accurate stock price predictions can lead to better investment decisions, risk management, and overall market efficiency. Financial institutions can leverage these models to develop advanced trading strategies and tools for market analysis.

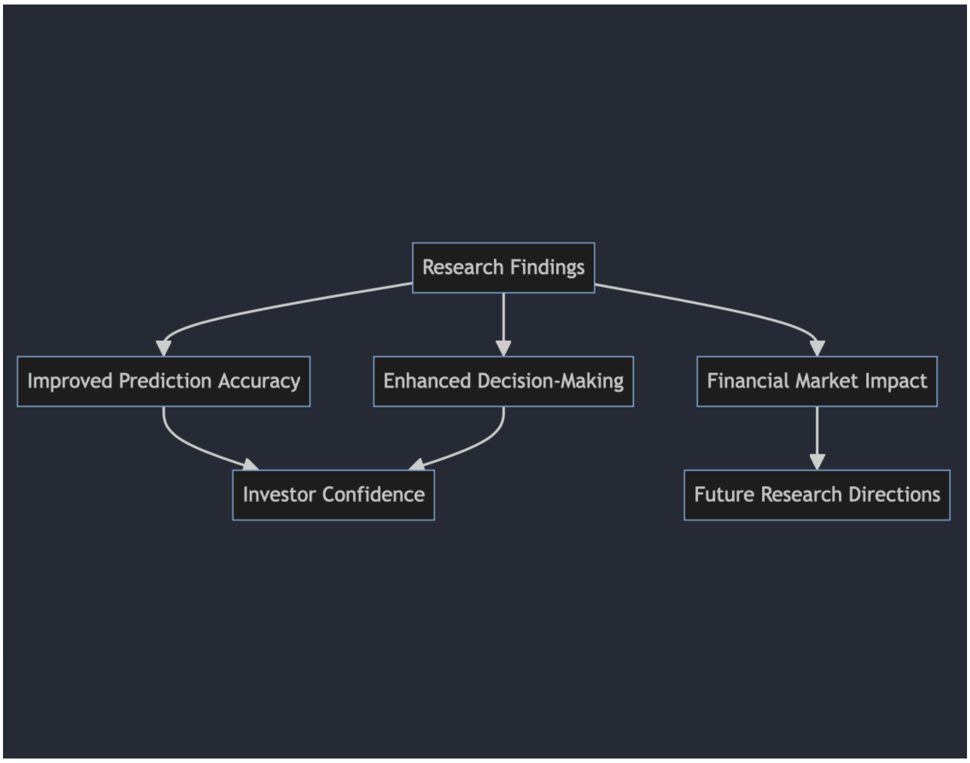

Figure 7.1: Implications of Research Findings

Chapter 8

Conclusion

8.1 Summary

In this study, we reviewed advanced machine learning techniques (LSTM) to understand their potential in predicting stock prices. The research indicated high potential in improving prediction accuracy and generalization capability. This work contributes to the field of financial time series forecasting by integrating technical indicators such as trendiness, support, and resistance levels.

8.2 Limitations

Despite the promising insights, the study faced several limitations:

- The insights are highly dependent on the quality and accuracy of the input data.
- Market conditions can change rapidly, and past performance may not always be indicative of future results.
- The study assumed that historical patterns and trends would repeat in the future, which may not always hold true.

8.3 Future Work

Future research can build on this study by:

- Implementing the models and findings into practical applications.
- Exploring additional technical indicators and alternative data sources such as social media sentiment and macroeconomic indicators.
- Enhancing the model by incorporating ensemble learning techniques and advanced architectures like Transformers.
- Developing a user-friendly interface for a practical implementation of these findings.
- Conducting a comprehensive analysis of the performance in different market conditions, including periods of high volatility and economic downturns.

8.3.1 Configuration of Input and Output Results

- **Input:** Our trained model (historical data prices) + current price (yfinance).
- **Output:**
  1. Expected stock movement.
  2. Graphing the (expected) trend, support, resistance, and adj lines.
  3. System specs: API connection method.

8.4 Research Gaps and Future Directions

Although there have been major improvements, there are still areas in the field that need attention. These include:

- The need for better models that can handle when the market is doing very well or very poorly.
- Including more information from other sources, such as social media and economic reports.
- Creating models using artificial intelligence that are easy to understand and explain.

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Appendices

Include any additional material that supports the report, such as raw data, additional graphs, or technical details.