" Stock Price Prediction: Integrating Linear and Deep Learning Approaches with Ensemble Techniques"

Statement of Originality

I declare that this dissertation, titled " Stock Price Prediction: Integrating Linear and Deep Learning Approaches with Ensemble Techniques" is the result of my own work and includes nothing which is the outcome of work done in collaboration, except as declared in the Acknowledgements and specified in the text.

This dissertation has not been submitted in whole or in part for any other academic award or qualification.

All sources used have been acknowledged through appropriate references using the Harvard referencing style.

Signed:

Geetal Nitin Kale

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Abstract

Stock price forecasting plays a vital role in financial decision-making, yet it remains a challenging task due to the non-linear, volatile, and dynamic nature of stock markets. This dissertation focuses on developing an effective predictive modelling framework to forecast the stock prices of Apple Inc. by leveraging both traditional machine learning and modern deep learning approaches. Conducted as part of the MSc in Data Science programme at the University of Sussex, the project aims to integrate various predictive techniques to improve accuracy and robustness in stock price predictions.

The study begins with a baseline Linear Regression model, which uses engineered features such as Exponential Moving Average (EMA), momentum, and lag values to capture linear relationships in the stock data. The dataset used comprises historical stock prices of Apple Inc., which are normalized and transformed into supervised learning sequences using a fixed lookback window.

To capture non-linear temporal dependencies, a Long Short-Term Memory (LSTM) neural network is developed using the Keras library. The LSTM model is further optimized using Keras Tuner, enabling automatic hyperparameter tuning to enhance performance.

To address the limitations of individual models, a Stacking Ensemble strategy is implemented. Predictions from both the Linear Regression and LSTM models are combined using two different meta-learners: a Decision Tree Regressor and XGBoost. While the Decision Tree provides a rule-based interpretation of model outputs, XGBoost is introduced due to its superior performance in handling complex patterns, regularization to prevent overfitting, and enhanced predictive capability.

All models are built and evaluated using Python programming tools including pandas, NumPy, scikit-learn, Keras, and XGBoost. Model performance is assessed using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The results indicate that the stacking ensemble with XGBoost outperforms all other approaches, providing more accurate and stable forecasts.

This dissertation demonstrates that combining traditional and deep learning models within a stacking ensemble framework can yield significant improvements in forecasting accuracy. The methodology developed offers a scalable and adaptable approach to financial time series prediction and contributes to ongoing research in the field of data-driven stock market analysis.

Chapter 1: Introduction

In the fast-paced and data-driven world of modern finance, accurately anticipating stock price movements is critically important. Stock market forecasting plays a crucial role in assisting investors, analysts, and financial institutions in making informed investment decisions. With the continuous growth in data availability and computational resources, predictive modelling has become a powerful tool in financial time series forecasting, enabling analysts to uncover patterns and relationships that traditional statistical models may fail to capture.

Advancements in artificial intelligence (AI) and machine learning (ML) have introduced sophisticated approaches for enhancing forecasting accuracy. These include deep learning models such as Long Short-Term Memory (LSTM) networks, which excel at capturing time-dependent patterns, and ensemble methods that combine predictions from multiple models to reduce variance and improve robustness (Zhang et al., 2020). The integration of such approaches has led to a paradigm shift in stock market forecasting research, enabling a move from purely statistical methods toward data-driven and adaptive forecasting systems.

This dissertation focuses on developing a predictive modelling framework that integrates both traditional machine learning and deep learning methods through ensemble learning techniques. Specifically, it investigates the forecasting of Apple Inc. stock prices using Linear Regression and LSTM as base models, combined via stacking with meta-learners such as Decision Tree Regressor and XGBoost. By leveraging the complementary strengths of linear and sequential models, this study aims to improve predictive accuracy and model generalization, contributing to ongoing advancements in financial forecasting research.

1.2 Stock Market Forecasting

Stock market forecasting involves predicting future stock price movements using historical price data and market indicators. Accurate predictions are valuable for investors and institutions in guiding investment decisions and managing risk. However, due to the market's volatility and sensitivity to a wide range of factors including economic indicators, news events, and investor sentiment forecasting remains a complex and uncertain task. Traditional models often struggle to capture these dynamic patterns, prompting increased interest in data-driven and machine learning approaches.

1.3 Predictive Modelling

Predictive modelling uses historical data to estimate future outcomes. In the context of this research, it involves forecasting stock prices using both linear and deep learning methods. Linear Regression offers simplicity and interpretability, while LSTM models are capable of capturing temporal patterns in sequential data. To enhance accuracy, ensemble learning techniques such as stacking are used to combine multiple models. This dissertation adopts a stacking framework that integrates Linear Regression and LSTM, aiming to leverage their complementary strengths for more reliable stock price forecasting.

1.4 Background

Stock Market Fundamentals and Forecasting Challenges

The stock market is a cornerstone of the global economy, providing a platform for capital formation and investment opportunities. Stock prices are influenced by a range of factors, including corporate earnings, macroeconomic indicators, investor sentiment, and geopolitical developments (Fama, 1970). Forecasting stock prices is challenging because markets are highly volatile and susceptible to unpredictable shocks.

Traditional forecasting approaches, such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing, have historically been applied to model stock prices (Tsay, 2010). While these methods provide interpretability, they are constrained by their reliance on linear assumptions and their inability to model complex and non-linear dependencies. The **Random Walk Hypothesis** further posits that price changes are largely stochastic and unpredictable, implying that past price movements cannot reliably forecast future prices (Malkiel, 1973).

Evolution of Predictive Modelling in Finance

Predictive modelling in finance has evolved significantly with the increased availability of market data and computational resources. Early approaches primarily involved linear regression and time series decomposition to model price patterns (Brooks, 2019). These models, however, were inadequate in handling abrupt market shocks and structural changes.

The incorporation of technical indicators such as Moving Averages (MA), Relative Strength Index (RSI), and Momentum improved model performance by quantifying trend strength and overbought/oversold conditions (Murphy, 1999). Despite this, linear models remained insufficient in capturing the inherent complexity of financial markets, paving the way for machine learning methods.

Role of Machine Learning in Stock Forecasting

Machine learning (ML) has transformed financial forecasting by employing data-driven algorithms that learn patterns without assuming specific functional relationships. Algorithms such as Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines (GBM) have been widely used to predict price movements with improved accuracy (Atsalakis & Valavanis, 2009). These methods excel in modelling high-dimensional datasets and non-linear dependencies.

However, static ML models often overlook the temporal structure of financial time series. Stock price data exhibit sequential dependencies where past information influences future movements. To address this, deep learning architectures such as Recurrent Neural Networks (RNNs) and their variants Long Short-Term Memory (LSTM) networks have been adopted for their ability to model sequential and time-dependent data (Hochreiter & Schmidhuber, 1997).

Deep Learning for Time Series Forecasting

Deep learning, particularly LSTM networks, has emerged as a powerful tool in time series forecasting. LSTMs overcome the vanishing gradient problem in RNNs, enabling them to capture both short-term fluctuations and long-term dependencies (Fischer & Krauss, 2018). These models learn complex, non-linear relationships within sequential data, making them highly suitable for volatile stock markets.

In addition to price data, LSTM models can incorporate engineered features such as momentum and moving averages to improve predictive accuracy. Despite their success, LSTMs require extensive tuning and are often criticised for their "black box" nature, which limits interpretability (Goodfellow et al., 2016).

2.5 Ensemble Learning in Financial Prediction

Ensemble learning methods aim to improve prediction accuracy by combining multiple models to balance their strengths and weaknesses. Common ensemble techniques include bagging, boosting, and stacking (Dietterich, 2000). In finance, ensemble models are particularly effective because they can integrate linear trend-capturing models with non-linear models that adapt to market volatility.

Stacking, a form of ensemble learning, involves training base models independently (e.g., Linear Regression and LSTM) and then feeding their outputs into a meta-learner (e.g., XGBoost) to generate final predictions (Zhou, 2012). Studies have demonstrated that ensemble strategies outperform individual models by reducing variance and overfitting while enhancing generalisation in stock price forecasting (Fischer & Krauss, 2018).

1.5 Research Problem

Forecasting stock prices remains one of the most challenging tasks in financial analysis due to the inherent volatility and complexity of the stock market. While traditional linear models such as Linear Regression are valued for their simplicity and interpretability, they often fail to capture the non-linear and dynamic patterns in financial time series. On the other hand, advanced deep learning models such as LSTM networks are highly effective at modelling sequential dependencies but require extensive computational resources and lack transparency in their decision-making process, limiting their practical applicability for many investors and analysts.

Despite significant advancements in machine learning and deep learning techniques, there is still no widely adopted framework that effectively integrates both linear and deep learning methods to achieve robust and accurate stock price forecasting. Existing studies tend to focus on individual model classes, either relying on traditional statistical models that oversimplify market dynamics or using deep learning models that, while powerful, can overfit or become too complex for practical deployment.

This presents a pressing problem: **how can we design a predictive modelling framework that leverages the strengths of both linear and deep learning approaches while mitigating their individual weaknesses?** Addressing this issue is essential not only for improving

predictive accuracy but also for developing models that are both interpretable and applicable in real-world financial decision-making contexts.

This dissertation seeks to address this problem by developing an ensemble-based predictive modelling framework that integrates Linear Regression and LSTM models within a stacking architecture. By introducing meta-learners such as Decision Tree Regressor and XGBoost, this approach aims to intelligently combine the outputs of different models to deliver more accurate, robust, and adaptable stock price forecast

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1.6 Research Gap

Stock market forecasting has been extensively studied using both statistical and machine learning techniques. Traditional linear models such as Linear Regression provide interpretability and perform well in capturing stable trends, but they struggle with non-linear relationships inherent in financial time series. In contrast, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong potential in modelling sequential dependencies and non-linear dynamics. However, despite their effectiveness, these models are prone to overfitting, require large amounts of data, and often act as "black boxes," limiting interpretability and practical adoption.

Recent research has explored ensemble learning approaches to combine different model types and leverage their individual strengths. While methods such as bagging and boosting have improved forecasting accuracy, there remains limited focus on integrating linear and deep learning models specifically for financial time series. Existing ensemble frameworks often rely on combining models of similar architecture (e.g., multiple neural networks or tree-based models), overlooking the potential of combining fundamentally different paradigms to exploit both trend-based linear patterns and complex temporal dependencies simultaneously.

Furthermore, there is a lack of studies that evaluate ensemble approaches using real-world, high-volatility stock data and benchmark their performance against individual models in a systematic manner. Although some hybrid methods have been proposed in literature, they often lack meta-learning frameworks such as stacking, where a meta-learner can intelligently learn how to weight and combine predictions from heterogeneous models.

This dissertation addresses this gap by integrating Linear Regression and LSTM models within a stacking ensemble, and employing Decision Tree and XGBoost meta-learners to intelligently

aggregate predictions. By focusing on Apple Inc. stock data, a widely traded and volatile stock, this study not only demonstrates the practical applicability of such techniques but also contributes to the limited body of research combining linear and deep learning approaches in financial forecasting within a meta-learning framework.

1.7 Research Aim and Objectives

The primary aim of this research is to develop a robust predictive modelling framework for stock price forecasting by integrating linear models and deep learning approaches within an ensemble learning architecture. The study specifically investigates whether a stacking ensemble comprising Linear Regression and Long Short-Term Memory (LSTM) models as base learners, and Decision Tree and XGBoost as meta-learners—can enhance predictive accuracy and model generalization when applied to real-world financial time series data.

To achieve this aim, the research sets out several key objectives. First, it seeks to construct and evaluate a baseline Linear Regression model using engineered stock market indicators such as the Exponential Moving Average (EMA), momentum, and lagged closing prices. Second, it involves the implementation and optimization of an LSTM model capable of capturing temporal and non-linear dependencies within historical stock price data. The third objective focuses on improving the performance of the LSTM through systematic hyperparameter tuning using Keras Tuner, ensuring greater accuracy and generalizability.

Following the development of individual models, the research then aims to design and test a stacking ensemble framework that intelligently combines the outputs of the Linear Regression and LSTM models through meta-learners specifically, the Decision Tree Regressor and XGBoost. This ensemble is expected to leverage the complementary strengths of linear and sequential modelling techniques. Additionally, the study intends to conduct a comparative analysis of all models individual and ensemble using standard evaluation metrics such as Root Mean Squared Error (RMSE) and Mean Squared Error (MSE). Finally, the research aims to assess the interpretability, robustness, and real-world applicability of the proposed ensemble forecasting approach within the context of high-volatility financial markets.

1.8 Research Scope and Focus

Building upon the identified research gap, this dissertation focuses on developing a **predictive modelling framework for stock price forecasting** that integrates both **linear and deep learning approaches within a stacking ensemble architecture**. The study specifically examines the stock price of **Apple Inc. (AAPL)** as a real-world case study, given its high trading volume, volatility, and significance in global markets.

The scope of this research encompasses three primary stages. First, a **Linear Regression model** is constructed using engineered financial indicators such as **Exponential Moving Average (EMA)**, momentum, and lagged closing prices to establish a baseline for capturing linear trends. Second, a **LSTM** network is implemented to learn temporal dependencies and sequential patterns inherent in stock price data, leveraging its ability to handle time-series forecasting effectively. The LSTM model undergoes **hyperparameter tuning** using Keras Tuner to optimize performance and generalization.

Finally, a **stacking ensemble framework** is applied, combining the outputs of the Linear Regression and LSTM models as input features for meta-learners specifically, **Decision Tree Regressor** and **XGBoost**. This meta-learning approach allows the ensemble to intelligently balance the strengths of both base models, improving robustness and reducing forecasting error.

The research evaluates each model and ensemble configuration using metrics such as **Mean Squared Error (MSE)** and **Root Mean Squared Error (RMSE)** to provide a comparative analysis of predictive accuracy. Through this methodology, the study aims to demonstrate how **integrating linear and deep learning models within an ensemble** can enhance stock market forecasting performance while maintaining practical applicability in real-world financial contexts.

1.9 Research Questions

This dissertation is guided by a series of research questions designed to evaluate the effectiveness of integrating linear and deep learning approaches within a predictive modelling framework for stock price forecasting. The first question explores the performance of a Linear Regression model in forecasting stock prices using engineered features such as EMA, momentum, and lag values. The second question investigates whether an LSTM model, with its ability to capture sequential dependencies, can outperform the baseline linear model in terms

of forecasting accuracy. The third research question examines the extent to which hyperparameter tuning influences the performance and generalization of the LSTM model.

Building on these individual models, the fourth question assesses the predictive accuracy of a stacking ensemble that combines Linear Regression and LSTM, compared to each model in isolation. The fifth question focuses on the impact of different meta-learners—specifically Decision Tree and XGBoost on the ensemble's ability to generalize and reduce forecasting error. Finally, the sixth question considers the interpretability, scalability, and real-world applicability of the proposed ensemble framework within financial decision-making contexts.

1.10 Structure of the Dissertation

The dissertation is structured into eight chapters as follows:

Chapter 1: Introduction
Introduces the motivation, background, research problem, gap, and objectives of the study. It sets the foundation by outlining the key components of the research.

Chapter 2: Background and Related Work
Reviews existing literature and theoretical foundations of stock market forecasting, linear and deep learning models, and ensemble learning techniques.

Chapter 3: Data
Describes the dataset used, including its source, characteristics, and exploratory data analysis. It also covers the preprocessing steps and feature engineering techniques applied.

Chapter 4: Methodology
Details the design and development of the predictive models, including the Linear Regression baseline, LSTM implementation, hyperparameter tuning, and ensemble strategies.

Chapter 5: Implementation
Outlines the technical implementation, including software tools, code structure, model configuration, and training/testing setup.

Chapter 6: Results
Presents and interprets the results of model evaluation and comparisons using appropriate metrics and visualizations.

Chapter 7: Conclusion and Future Work

Summarizes the key findings, discusses the limitations of the study, and proposes directions for future research.

Chapter 8: References

Provides a list of all scholarly sources cited throughout the dissertation, formatted according to Harvard style.

Chapter 2: Background and Related Work

2.1 Introduction

This chapter outlines the theoretical and methodological foundations that support the implementation of predictive models for stock market forecasting. It begins with a theoretical background covering the essential concepts and techniques used in this study, including financial time series forecasting, linear regression, LSTM networks, and ensemble learning approaches such as stacking. These foundations are critical for understanding the motivations behind model selection and the integration strategies employed in this project.

The second half of this chapter presents a review of related work in the field of stock price forecasting, summarising key studies that have applied both traditional machine learning and deep learning techniques to time series data in financial domains. This includes a critical analysis of existing research efforts and highlights the methodological gaps that this dissertation seeks to address through an integrated predictive modelling approach.

2.2 Theoretical Background

This section introduces the essential models, concepts, and techniques used in the development of the forecasting framework.

2.2.1 Stock Price Forecasting as a Time Series Problem

Stock price forecasting is fundamentally a time series prediction task where the objective is to estimate future values based on previously observed data points. Financial time series data, such as daily stock closing prices, are inherently complex due to their non-linear, non-stationary, and volatile nature.

Unlike deterministic systems, the stock market is influenced by a multitude of interdependent factors such as macroeconomic indicators, investor sentiment, geopolitical events, and company-specific performance metrics. These variables contribute to unpredictable fluctuations and noise in the time series, making accurate forecasting a challenging endeavour.

The non-stationary nature of financial data means that the statistical properties (such as mean and variance) change over time. Additionally, financial time series often exhibit autocorrelation, volatility clustering, and sudden structural breaks. These challenges necessitate advanced predictive techniques capable of capturing temporal dependencies and adaptive patterns in the data.

2.2.2 Linear Regression for Forecasting

Linear regression is one of the most fundamental and widely used statistical methods for predictive modelling. It operates under the principle of modelling the relationship between a dependent variable (target) and one or more independent variables (predictors) by fitting a linear equation to observed data. In the context of stock price forecasting, the goal is to predict future prices based on historical values and other influencing factors, assuming a linear relationship between these variables.

The basic form of linear regression is expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \epsilon$$

where:

- y is the predicted stock price (dependent variable),
- $x1, x2, \ldots, xn$ are the input features (independent variables),
- β0 is the intercept,
- β1, …, βn are the coefficients representing the impact of each feature,
- ϵ is the error term.

Linear regression is appreciated for its simplicity, interpretability, and computational efficiency. It allows analysts to quantify the strength and direction of relationships between variables, which is particularly useful in financial domains where interpretability is critical for

decision-making.

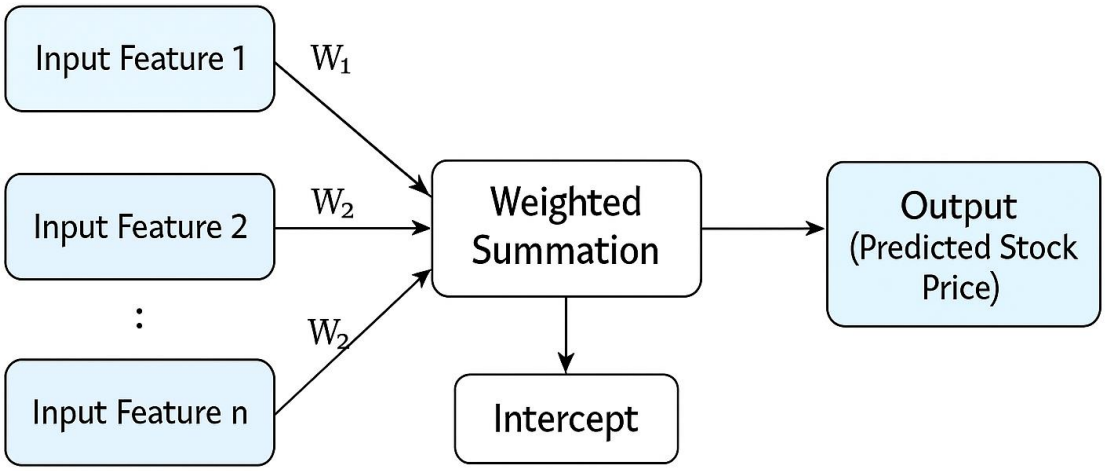

Figure 2.1: Linear Regression Architecture for Stock Price Forecasting

Figure 2.1 illustrates the architecture of a linear regression model where input features (e.g., previous stock prices, technical indicators) are passed through a weighted summation process. These inputs are multiplied by their respective coefficients, summed with an intercept term, and produce a single continuous output — the predicted stock price. The model is trained to minimise the error between predicted and actual prices, typically using Mean Squared Error (MSE) as the loss function.

Strengths in Financial Forecasting: One of the key strengths of linear regression in financial forecasting is its transparency. The model's coefficients offer clear and interpretable insights into how each input feature influences the target variable, which can be valuable for analysts seeking to understand the underlying drivers of stock price movements. Additionally, linear regression is highly efficient; it trains quickly and requires minimal computational resources, making it ideal for developing rapid baseline models. Another advantage lies in its suitability for small datasets. Unlike more complex models that demand large amounts of data to perform well, linear regression can deliver usable results even when historical stock data is limited, which is often the case with certain financial instruments or newly listed companies.

Limitations in Financial Forecasting: Despite its simplicity and interpretability, linear regression has several limitations when applied to financial forecasting. One major drawback is its assumption of a linear relationship between independent variables and the target, which often does not hold true in the highly complex and non-linear nature of financial markets. Stock prices are influenced by a multitude of factors, including market sentiment, geopolitical events, and macroeconomic indicators, which interact in ways that linear models cannot adequately capture. Furthermore, linear regression

is sensitive to outliers and multicollinearity, both of which are common in financial datasets. These issues can distort the model's predictions and reduce its robustness. Consequently, while useful as a starting point, linear regression is often outperformed by more sophisticated models capable of capturing non-linear patterns and complex feature interactions.

2.2.3 LSTM and Deep Learning in Time Series

Concept of RNNs and Motivation for LSTM: Stock price forecasting presents a significant challenge due to the sequential and highly volatile nature of financial data. Patterns often span across different time intervals, meaning that any predictive model must be able to capture temporal dependencies. Traditional feedforward neural networks are unable to maintain memory of previous inputs, making them inadequate for such tasks. Recurrent Neural Networks (RNNs) were developed to overcome this limitation by introducing recurrent connections that allow information to persist across time steps.

RNNs are capable of learning from sequential data by maintaining a hidden state vector that evolves as new inputs are introduced. However, standard RNNs face serious limitations when dealing with long sequences. The primary challenge is the **vanishing and exploding gradient problem**, which hinders the ability of the network to learn long-term dependencies. This issue is particularly critical in stock price forecasting where market trends may unfold over extended timeframes.

To mitigate these limitations, **Long Short-Term Memory (LSTM)** networks were introduced. LSTM is a specialized form of RNN designed to retain long-term information more effectively. It incorporates a gated architecture that allows the network to learn when to forget, retain, or output information. This makes LSTM particularly well-suited for time series problems such as stock forecasting.

LSTM Architecture (Memory Cells and Gates): The LSTM architecture is designed around the concept of a **cell state**, which serves as a conveyor belt that carries information throughout the sequence. This structure allows the model to maintain long-term memory while also controlling the flow of new inputs and forgetting irrelevant information.

The key components of an LSTM cell include the **Forget Gate (σf)**, which decides which information from the previous cell state should be discarded, and the **Input Gate (σi)**, which determines what new information should be added to the cell state. The **Candidate State (tanh)** proposes potential new values that can be integrated into the state, while the **Output Gate (σo)** regulates which part of the cell state should be output to the next time step. These components work together through element-wise operations, such as multiplications and additions, and make use of activation functions like the sigmoid (σ) and hyperbolic tangent (tanh) to effectively control the flow of information within the LSTM cell.

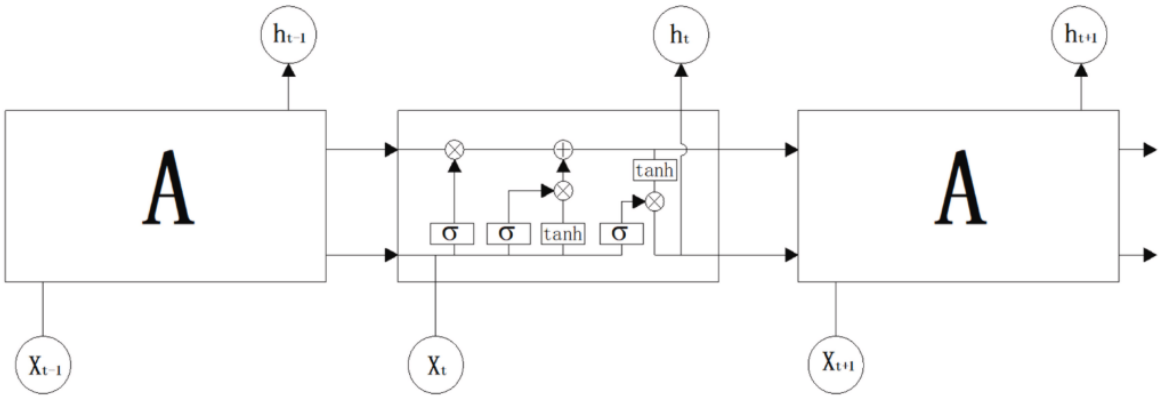

Figure 2.2: LSTM Architecture

Figure 2.2 illustrates the internal flow of information through gates and memory cells across time steps, In this figure, the horizontal line represents the cell state, which flows through the entire sequence with minor linear interactions. The vertical lines represent the input, forget, and output gates that interact with the cell state. The symbols inside the central block (e.g., σ and tanh) represent the gating functions and activations responsible for updating the cell's memory and hidden state ht.

Why LSTM is Well-Suited for Stock Forecasting?

LSTM networks are particularly well-suited for stock price forecasting due to several key advantages. Firstly, they excel at handling long-term dependencies, enabling them to retain crucial information across extended sequences, which is essential for capturing delayed market responses and long-term trends something traditional RNNs often struggle with. Additionally, LSTMs are adept at modelling non-linearity and complexity, allowing them to learn intricate, non-linear relationships inherent in stock price movements that are influenced by various latent factors, without the need for extensive feature engineering. Their tolerance to noise is another significant strength, as financial data is inherently noisy, and LSTMs can effectively learn robust patterns while filtering out short-term fluctuations that do not contribute meaningfully to forecasts. Furthermore, LSTMs require minimal preprocessing, as they can operate on raw or minimally processed time series data, eliminating the need for manually crafted lag features or moving averages that are often necessary in traditional time series models. Owing to these capabilities, LSTMs have gained popularity in financial forecasting research and, when combined with other models in ensemble learning strategies, contribute substantially to enhancing predictive accuracy**.**

2.2.4 Ensemble Learning Techniques

Overview of Ensemble Learning

Ensemble learning is a machine learning paradigm where multiple models often called weak learners are strategically combined to produce a more accurate and robust prediction than any single model could achieve alone. The underlying principle is that diverse models can compensate for each other's individual errors, thus improving generalization. Ensemble methods are widely used in both classification and regression tasks, and they have shown exceptional performance in complex, real-world problems such as stock price forecasting.

By aggregating the outputs of multiple models, ensemble methods reduce variance (which affects overfitting), bias (which affects underfitting), or improve predictions through more intelligent model combinations. These techniques are particularly effective when different models capture different patterns or structures within the data, which is often the case in volatile and noisy financial datasets.

Difference Between Bagging, Boosting, and Stacking

There are several types of ensembles learning techniques, with **bagging**, **boosting**, and **stacking** being among the most widely used. **Bagging** (Bootstrap Aggregating) involves training multiple models independently on different bootstrapped subsets of the original dataset i.e., samples drawn randomly with replacement. The predictions from these models are then aggregated by averaging (for regression) or majority voting (for classification). This approach primarily helps reduce variance and mitigate overfitting, and a well-known example is the Random Forest algorithm. In contrast, **boosting** trains models sequentially, where each new model attempts to correct the errors made by the previous ones. In this method, greater focus is placed on misclassified or poorly predicted data points by adjusting their weights, thereby reducing bias and improving model accuracy. Notable boosting algorithms include AdaBoost, Gradient Boosting. **Stacking**, or stacked generalization, takes a fundamentally different approach by training multiple diverse base learners (also known as level-0 models) and then combining their outputs using a meta-learner (level-1 model). Unlike bagging or boosting, stacking doesn't just aggregate the outputs it learns how to best combine the predictions based on the strengths and weaknesses of each base learner. When configured effectively, stacking can often outperform both bagging and boosting methods.

Stacking Architecture and Role of Base vs. Meta Learners

In stacking, the architecture is organized into two levels that is base learners and a meta-learner. The **base learners** constitute the first layer and are trained directly on the original dataset. These models can be of different types such as linear regression, LSTM, or decision trees enabling the ensemble to

learn from a variety of perspectives and strategies. The predictions generated by these base models are then used as input features for the next stage. At the second layer, the **meta-learner** is trained on these outputs to learn how to best combine or weigh the base learner's predictions to produce a final result. The meta-learner can range from a simple linear regression model to more advanced techniques such as decision trees or gradient boosting regressors. This two-tier structure allows stacking to capture a wider array of patterns within the data. In this project, for instance, the base model's linear regression and LSTM are used to capture linear and temporal dynamics respectively, while the meta-learner, such as XGBoost or a decision tree, synthesizes these insights for final prediction. By combining the complementary strengths of multiple algorithms, stacking significantly enhances predictive performance, especially in complex and volatile environments like stock market forecasting.

Stacking Flowchart:

Figure 2.3 illustrate the flow of stacking ensemble method it consists of two levels. The first level comprises base learners, which are individual models trained on the original training dataset. These base models may use different algorithms, such as Linear Regression and LSTM, which were adopted in this project to capture both linear and temporal patterns, respectively (Hochreiter and Schmidhuber, 1997; Brownlee, 2017). The second level features a meta-learner that is trained on the outputs (predictions) of the base learners. This meta-learner learns how to best combine these predictions to produce a final output (Wolpert, 1992). In this project, meta-models like Decision Tree Regressor and XGBoost were used to integrate the outputs of the base learners into a unified forecast, leveraging both interpretability and high performance (Chen and Guestrin, 2016). The advantage of stacking lies in its ability to exploit the strengths and minimize the weaknesses of individual models, leading to improved generalization performance across diverse datasets (Sagi and Rokach, 2018). This is particularly beneficial in complex domains like stock market forecasting, where patterns may be nonlinear, volatile, and difficult to model with a single approach.

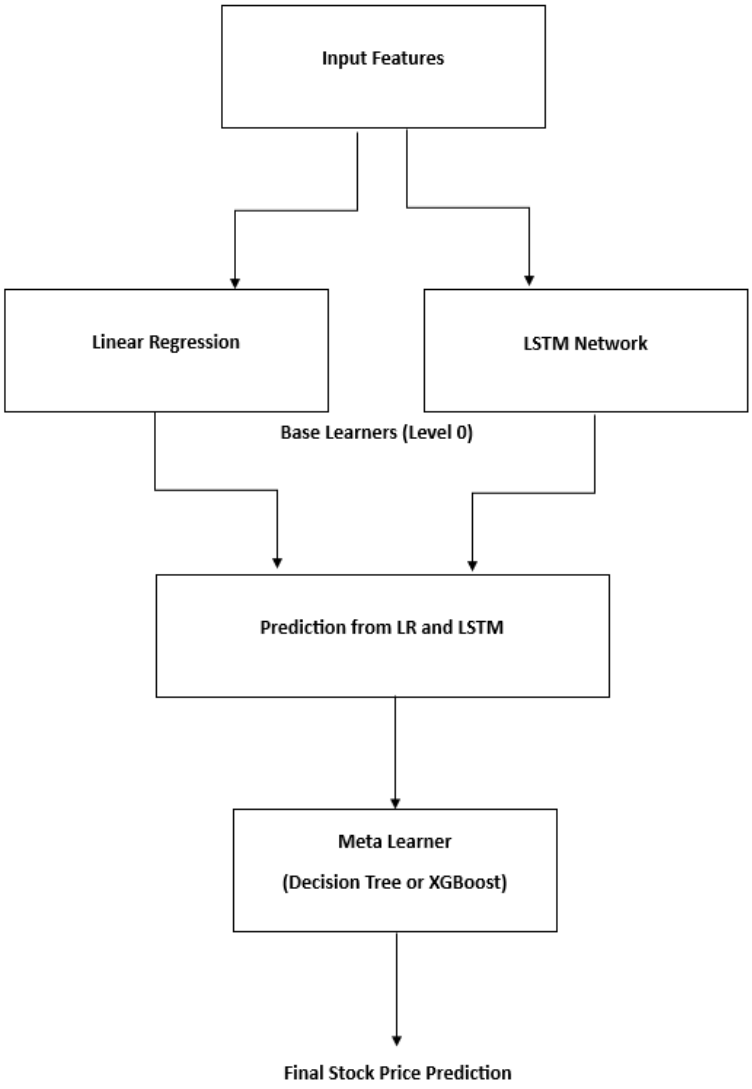

Figure 2.3: Stacking Flowchart

2.2.6 Role of Meta Learners in Stacking: Decision Tree and XGBoost

In a stacking ensemble, meta learners play a crucial role in combining the predictions from base models to produce a final, more accurate forecast. Two meta learners explored in this project are the **Decision Tree Regressor** and **XGBoost**, chosen for their complementary strengths.

The **Decision Tree Regressor** is a simple yet powerful model that splits the data based on feature values to capture non-linear relationships. Its interpretability and low computational cost make it an appealing meta-learner. However, decision trees are prone to overfitting, especially in noisy or high-variance datasets, which can limit their generalizability in financial forecasting.

To overcome this, **XGBoost** was employed as an alternative meta learner. XGBoost is a gradient boosting algorithm that builds an ensemble of weak decision trees in a sequential manner, optimizing the model through regularization and loss minimization. It offers improved accuracy, robustness to noise, and better generalization performance. These capabilities make XGBoost particularly effective in refining and aggregating the outputs from

diverse base learners like Linear Regression and LSTM, enhancing the overall predictive performance of the stacking model.

2.3 Literature Review and Related Work

This section presents an overview of past research and methodologies applied to stock price forecasting. It covers traditional statistical models, machine learning approaches, and modern deep learning techniques, highlighting their strengths, limitations, and relevance to this study.

2.3.1 Traditional Approaches to Stock Forecasting

Stock market forecasting has historically relied on traditional statistical and machine learning techniques such as Linear Regression, ARIMA (AutoRegressive Integrated Moving Average), and Support Vector Machines (SVM). These models were widely adopted due to their interpretability, simplicity, and relatively low computational requirements. However, the inherently complex, non-linear, and noisy nature of financial time series data poses significant challenges to these approaches. **Linear regression** is one of the earliest and most widely used models in financial forecasting. It models the relationship between a dependent variable (e.g., future stock price) and one or more independent variables (e.g., previous prices, technical indicators) by fitting a linear equation to the observed data (Gujarati and Porter, 2009). Its primary strength lies in its interpretability; the coefficients provide a direct understanding of how each predictor influences the target variable. Additionally, it performs well on small datasets and requires minimal training time.

However, linear regression assumes a linear relationship between variables and homoscedasticity, which are rarely satisfied in real-world stock data. Financial markets are influenced by multiple dynamic and interacting factors that lead to non-linearity, volatility clustering, and structural breaks, all of which degrade the performance of a linear model (Tsai and Hsiao, 2010). Moreover, linear regression is sensitive to outliers and multicollinearity, both of which are common in financial datasets. **ARIMA** is a popular statistical method specifically designed for time series forecasting. It combines autoregression (AR), differencing (I), and moving average (MA) to capture trends and autocorrelations in stationary time series data (Box et al., 2015). The strength of ARIMA lies in its ability to model short-term dependencies and temporal dynamics, making it suitable for univariate forecasting when the series is stationary or can be made stationary through differencing.

Despite its strong theoretical foundation, ARIMA is limited in its applicability to financial forecasting. First, the model requires stationarity, yet most financial time series are non-stationary, volatile, and influenced by exogenous variables that ARIMA cannot directly handle. Additionally, ARIMA is linear by design, thus incapable of capturing non-linear patterns often present in stock prices (Makridakis et al., 1998). It also struggles with multivariate time series, limiting its flexibility for incorporating macroeconomic indicators or other technical signals. **Support Vector Machines (and its extension**

for regression, SVR) are supervised learning models that use a kernel trick to handle non-linear relationships in high-dimensional spaces (Cao and Tay, 2003). SVR has been effectively applied in stock forecasting for modelling non-linear patterns and handling high-dimensional data. It is particularly robust to overfitting in small to medium-sized datasets due to its margin-maximization principle.

Nevertheless, SVMs come with notable limitations. They are computationally intensive, especially with large datasets, making real-time forecasting difficult. Moreover, their performance is highly sensitive to the choice of hyperparameters and kernel functions, often requiring extensive cross-validation (Tay and Cao, 2001). SVMs also lack transparency in their decision-making, which reduces their interpretability, a key requirement in financial analysis. So, while traditional methods like linear regression, ARIMA, and SVM provide foundational insights into stock forecasting, they struggle to capture the non-linear, noisy, and non-stationary nature of financial markets. These limitations have motivated the shift toward more sophisticated models such as deep learning and ensemble learning, which offer improved performance and adaptability.

2.3.2 Deep Learning for Financial Forecasting

The limitations of traditional models in capturing the non-linear and dynamic nature of financial markets have led to the growing adoption of deep learning approaches in stock price forecasting. Unlike linear models, deep learning methods are capable of learning complex temporal dependencies and feature hierarchies from raw data, making them well-suited for financial time series prediction.

Recurrent Neural Networks (RNNs) and LSTM

Recurrent Neural Networks (RNNs) are designed to process sequential data by maintaining a hidden state that captures information from previous time steps. This makes them particularly applicable to time series tasks, including financial forecasting. However, standard RNNs suffer from the **vanishing gradient problem**, which hampers their ability to learn long-term dependencies (Bengio et al., 1994).

To overcome this, **LSTM (Long Short-Term Memory)** networks were introduced, featuring a memory cell and gating mechanisms (input, forget, and output gates) that enable the model to retain and update information over longer sequences (Hochreiter and Schmidhuber, 1997). LSTM has shown superior performance in financial applications, such as stock price prediction, volatility forecasting, and risk assessment, due to its ability to capture both **short-term trends and long-range dependencies** in data.

Studies such as Fischer and Krauss (2018) have demonstrated that LSTM models significantly outperform traditional models and shallow machine learning methods in terms of prediction accuracy and adaptability to different market conditions.

Advantages and Limitations

The primary advantage of LSTM in stock forecasting lies in its **ability to model non-linear, non-stationary patterns** without the need for extensive feature engineering. Moreover, LSTMs are robust to noise and capable of learning directly from raw sequences of prices or returns, making them ideal for end-to-end predictive tasks (Nelson et al., 2017).

However, deep learning methods also come with **challenges**. They require **large volumes of data** to generalize well, and their training is **computationally intensive**. Additionally, deep models are often criticized for being **black-box systems**, which limits their interpretability — a critical concern in financial decision-making contexts

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2.3.3 Ensemble Learning Approaches in Stock Forecasting

Ensemble learning has emerged as a powerful paradigm in stock market forecasting, aiming to improve predictive accuracy by combining the strengths of multiple models. Unlike traditional single-model approaches, ensemble techniques integrate several base learners to reduce variance, bias, or improve predictions by leveraging diverse perspectives of the data. Common ensemble strategies include bagging, boosting, and stacking, each with distinct methodological advantages for capturing the nonlinear, noisy, and dynamic behaviour of financial time series. **Bagging** (Bootstrap Aggregating) creates multiple versions of a predictor by training each on a randomly resampled subset of the dataset. The final output is typically the average prediction (for regression tasks) or majority vote (for classification), leading to reduced variance and improved stability. Random Forest is a classic example of a bagging-based algorithm that has been used in stock forecasting to handle high-dimensional data and prevent overfitting (Durgapal and Vimal, 2021). **Boosting**, on the other hand, builds models sequentially, where each subsequent learner attempts to correct the errors of its predecessor. Algorithms like AdaBoost, Gradient Boosting, and XGBoost have been shown to perform exceptionally well in financial prediction tasks due to their ability to focus on hard-to-predict patterns and reduce both bias and variance (Sun et al., 2018). XGBoost, in particular, has gained widespread popularity for its regularization mechanisms and scalability, making it suitable for large financial datasets.

Stacking (stacked generalization) is a more complex ensemble technique that combines predictions from heterogeneous base models (level-0 learners) using a meta-learner (level-1 model). This

approach aims to capitalize on the unique strengths of each base model and correct their weaknesses through a learning-based integration. For instance, a stacking ensemble might combine a linear regression model to capture linear trends, an LSTM model to account for temporal dependencies, and a decision tree to model non-linear interactions. These outputs are then fed into a meta-model—such as XGBoost or another regressor—that learns the optimal combination of predictions.

Recent studies underscore the efficacy of stacking ensembles in stock price forecasting. Mozaffari and Zhang (2024) found that a stacking model combining Transformer and Linear Regression outperformed individual models, achieving a Mean Absolute Percentage Error (MAPE) as low as 2.24%. Similarly, other works have shown that ensembles integrating ARIMA with deep learning models improve robustness and reduce generalization errors across various stock indices (Chu et al., 2022; Durgapal and Vimal, 2021).

A key advantage of ensemble learning in financial applications is its ability to integrate both statistical and machine learning models. For example, ARIMA can effectively model short-term linear trends, while neural networks or tree-based models capture non-linear and long-range dependencies. When stacked, these models offer a holistic understanding of market behaviour, resulting in more accurate and resilient forecasts.

However, ensemble methods come with challenges such as increased computational complexity and the need for careful model selection and hyperparameter tuning. Overfitting can also occur if the base models or the meta-learner are not properly regularized. Despite these drawbacks, ensemble learning remains a compelling approach in financial forecasting due to its demonstrated ability to consistently outperform individual models, particularly in volatile and non-stationary environments like the stock market.

2.3.4 Gaps Identified and Contribution of This Study

Despite the progress in stock market forecasting, many existing models still have clear limitations. Traditional methods like ARIMA and Linear Regression are simple and easy to interpret, but they often fall short when it comes to capturing the complex, non-linear, and volatile nature of stock prices (Tsay, 2010). Deep learning models, especially LSTM, can model these complexities well — but they're typically used in isolation, and their black-box nature makes them harder to trust and explain (Fischer and Krauss, 2018; Goodfellow et al., 2016).

Ensemble methods have started to bridge this gap by combining the strengths of different models, but most existing studies tend to stick with similar types of models — such as only combining deep

learning models, or only statistical ones (Mozaffari and Zhang, 2024). What's often missing is a hybrid approach that combines very different types of models — like one that captures linear trends and another that handles time-based patterns — to make the most of both worlds. Also, many studies test their methods on broad indices rather than individual stocks, which doesn't always reflect the real challenges of forecasting highly traded and volatile stocks like Apple Inc.

This project addresses those gaps by building a **stacking ensemble** that combines **Linear Regression** and **LSTM** as base models, and uses **Decision Tree** and **XGBoost** as meta-learners. This setup is designed to capture both linear and sequential dynamics in the data, while also improving generalization and reducing forecasting error. By using a real-world dataset focused on Apple's stock and evaluating performance across key metrics, the study aims to show how a hybrid stacking framework can produce more accurate, robust, and practical forecasts. Ultimately, this research contributes to a growing area of work that blends interpretability, accuracy, and real-world applicability in financial forecasting.

Chapter 3: Data

3.1 Introduction

Data serves as the foundation of any data-driven forecasting model, especially in the domain of financial time series. This chapter provides an in-depth overview of the dataset used in the study, the rationale behind selecting Apple Inc. (AAPL) as the focus stock, and the steps taken to prepare the data for predictive modelling. The Apple stock data was retrieved using the yfinance API, ensuring up-to-date and high-quality financial information from January 1, 1995, to the present day. This extensive time frame offers the opportunity to capture long-term trends and patterns, which are essential for models such as LSTM that rely heavily on historical context. The chapter further explores data preprocessing techniques, exploratory data analysis (EDA), feature engineering, correlation analysis, and feature importance evaluation using SHAP values. Each of these steps plays a crucial role in shaping a reliable and interpretable model.

3.2 Data Source and Collection

The stock data used in this research was collected using the yfinance Python library, which allows easy access to historical market data from Yahoo Finance. Apple Inc. (ticker: AAPL) was selected for its high liquidity, substantial historical data availability, and relevance in the global financial market. The dataset includes daily observations comprising key features such as Open, High, Low, Close and Volume. These attributes offer a comprehensive view of daily trading activity and price dynamics. The

choice to begin the data from 1 January 1995 provides nearly three decades of observations, ensuring that both long-term trends and short-term fluctuations can be captured. The end date of the data dynamically reflects the current day of extraction, making the dataset always up to date at the time of modelling.

3.3 Initial Data Inspection and Preprocessing

Following data extraction, preliminary inspection was performed to understand the structure and quality of the dataset. Using the .info() method in pandas, it was confirmed that the data types were appropriately defined and that the time index was formatted correctly as a datetime object. Null values were present in some of the columns and were removed using .dropna() to ensure the integrity of the dataset. Given the importance of clean and consistent data in machine learning workflows, additional preprocessing included resetting the index and rounding values where appropriate to minimize computational noise. These steps were critical for preparing the dataset for subsequent feature engineering and model training phases.

3.4 Exploratory Data Analysis (EDA)

To better understand the underlying structure and dynamics of the stock price data, a detailed exploratory data analysis (EDA) was performed. This process helped uncover key statistical properties, temporal patterns, and market behaviours, thereby informing the subsequent feature engineering and model design phases.

Index (['Close', 'High', 'Low', 'Open', 'Volume'],

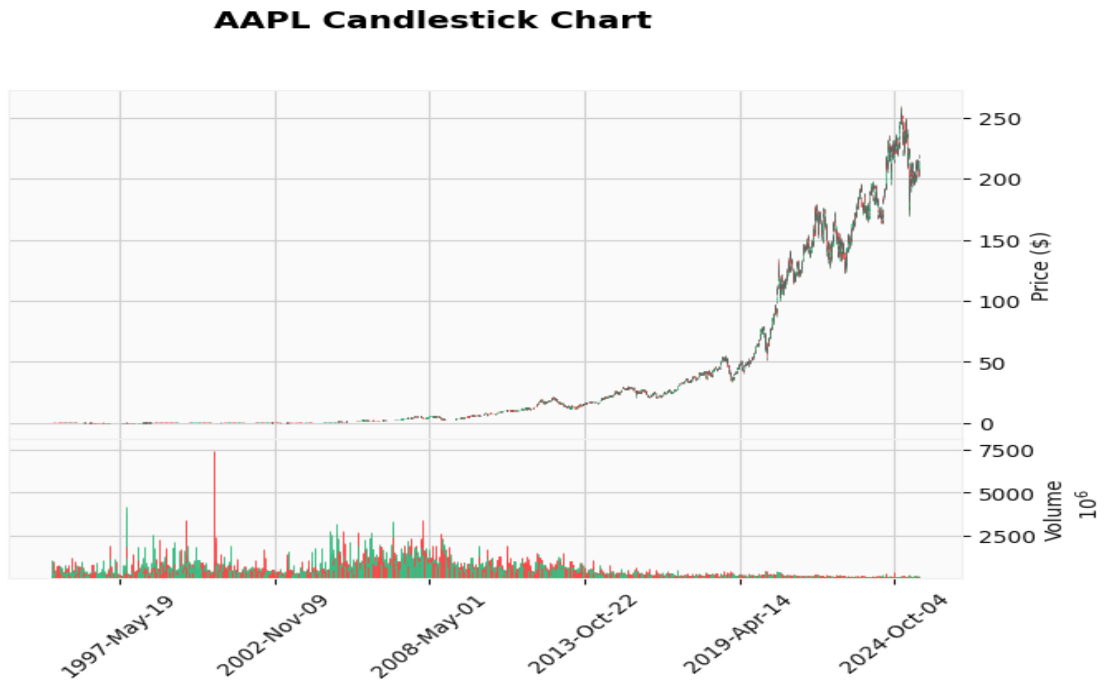


Figure 3.1: Candlestick Chart of Apple Stock

The first step in the EDA involved generating a **candlestick chart** for Apple Inc. using the mplfinance library. **Figure 3.1** illustrates this candlestick chart, which provides a detailed view of the stock's price movements across different time intervals, capturing the open, high, low, and close prices. This representation enabled the clear identification of **bullish and bearish trends** as well as short-term market reversals, making it particularly valuable for understanding investor sentiment and market volatility (Murphy, 1999).

Figure 3.2: Line Plot of Apple's Historical Closing Prices

Figure 3.2 presents the line plot of Apple's historical closing prices, illustrating the long-term trajectory of the stock. This visualisation highlights distinct periods of sustained growth and market corrections, underscoring the inherent volatility and non-stationary characteristics of financial time series. The general upward trend, punctuated by episodes of decline, reflects both broader economic cycles and company-specific events that have influenced Apple's market valuation over time.

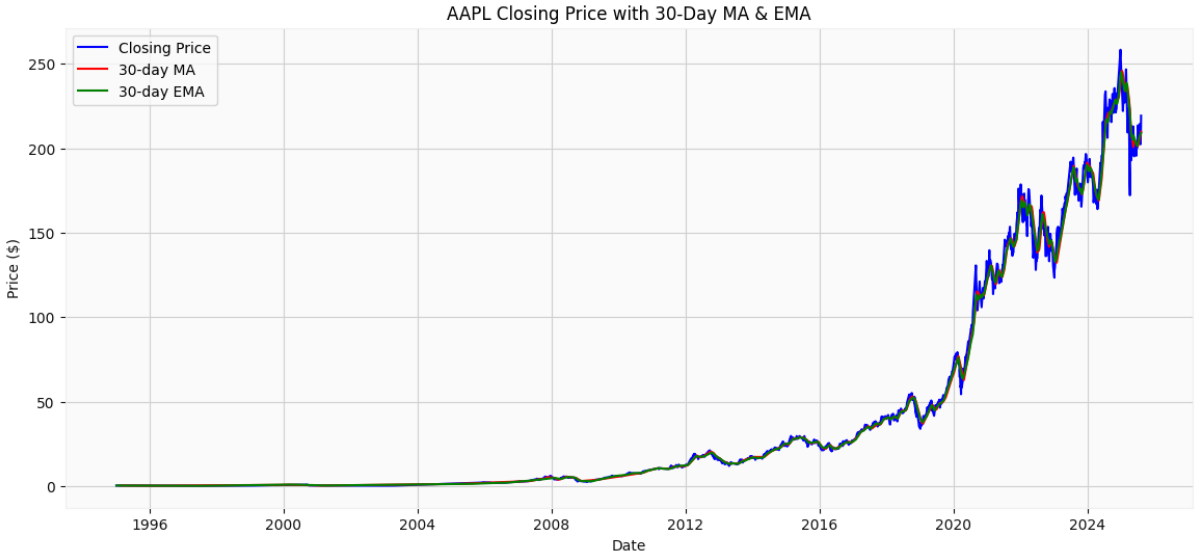
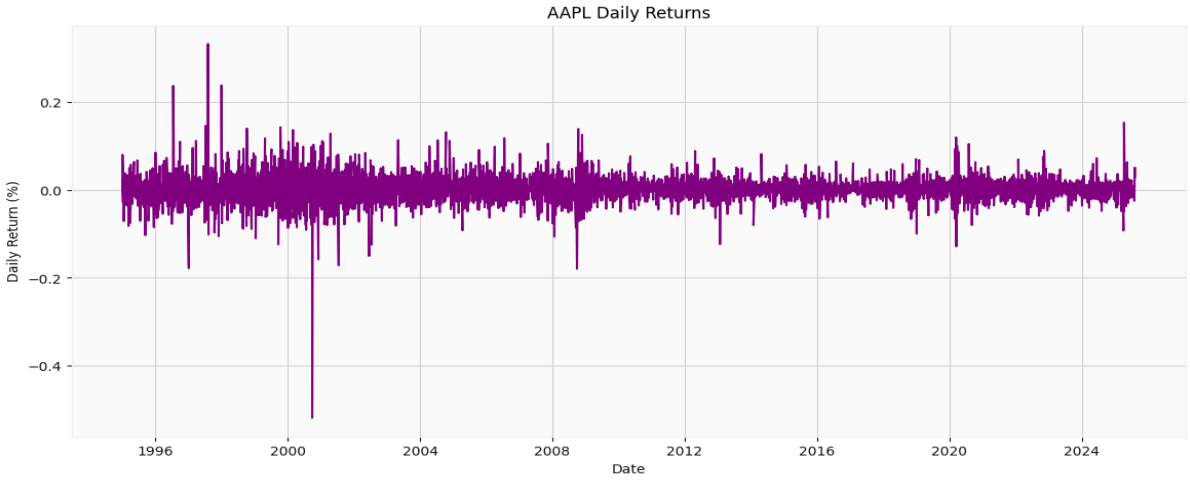


Figure 3.3: Closing Price with Moving Average and EMA Overlays

Figure 3.2 presents the line plot of Apple's historical closing prices, illustrating the long-term trajectory of the stock. This visualisation highlights distinct periods of sustained growth and market corrections, underscoring the inherent volatility and non-stationary characteristics of financial time series. The general upward trend, punctuated by episodes of decline, reflects both broader economic cycles and company-specific events that have influenced Apple's market valuation over time.



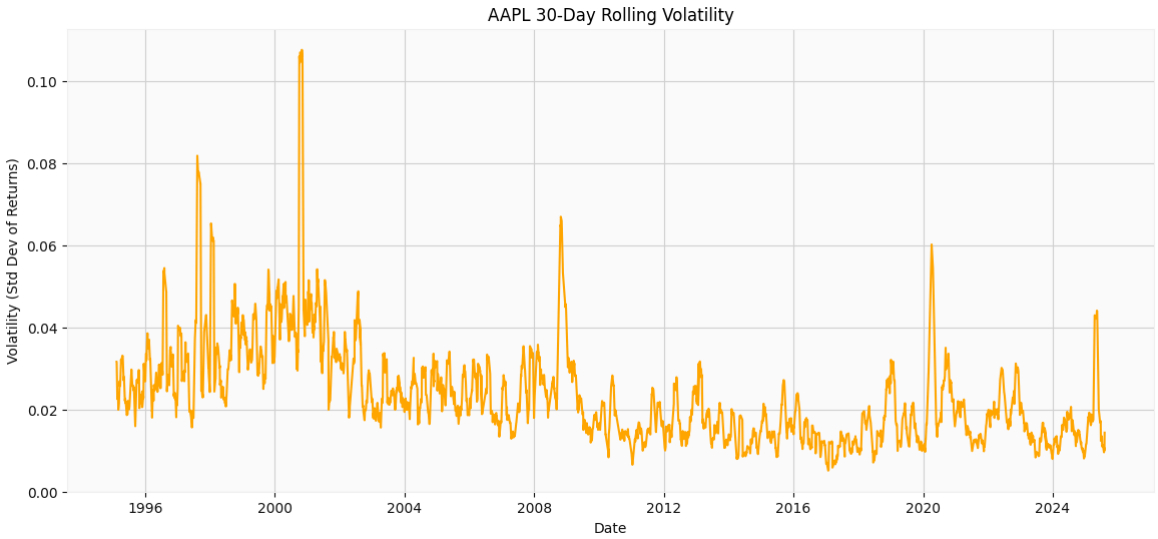


Figure 3.4: Daily Returns and 30-Day Rolling Volatility

Figure 3.4 illustrates the daily returns of Apple's stock alongside a 30-day rolling standard deviation, which serves as a proxy for historical volatility. The daily returns plot highlights the dispersion of price changes, while the rolling volatility measure identifies periods of heightened uncertainty, often coinciding with macroeconomic events or company-specific announcements. This combined view provides valuable insight into the clustering of volatility, a common characteristic in financial time series that must be accounted for in predictive modelling.

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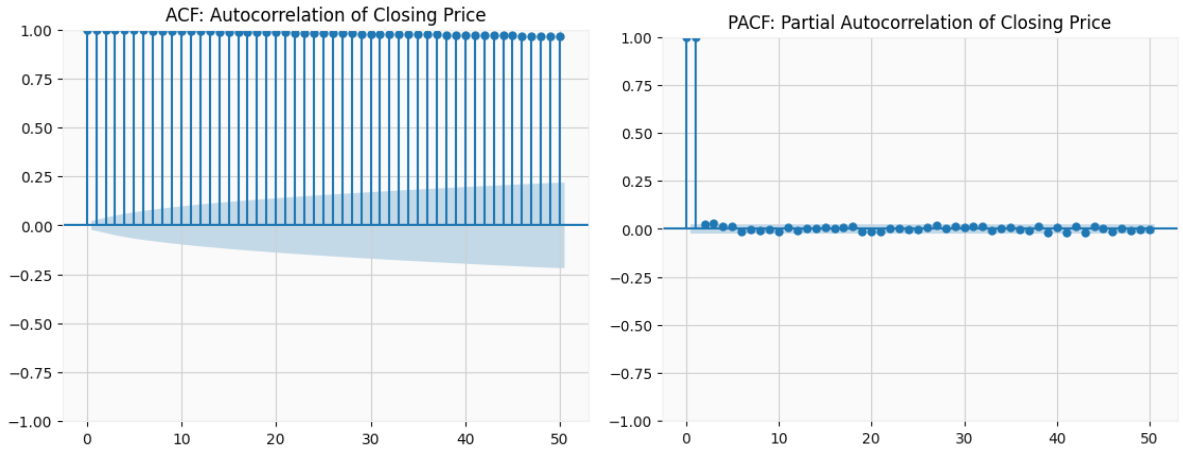

Figure 3.4: Daily Returns and 30-Day Rolling Volatility

Figure 3.4 illustrates the daily returns of Apple's stock alongside a 30-day rolling standard deviation, which serves as a proxy for historical volatility. The daily returns plot highlights the dispersion of price changes, while the rolling volatility measure identifies periods of heightened uncertainty, often coinciding with macroeconomic events or company-specific announcements. This combined view

provides valuable insight into the clustering of volatility, a common characteristic in financial time series that must be accounted for in predictive modelling. Together, these visualizations provided comprehensive insights into the dataset's structure, volatility patterns, and temporal dynamics, guiding the selection of relevant features and shaping the forecasting model design.

3.5 Feature Engineering

Feature engineering was conducted to enhance the predictive capacity of the forecasting models by extracting informative signals from the raw stock price data. In financial time series analysis, engineered features often encapsulate trends, momentum, and volatility patterns that are not immediately apparent from the original price series (Pang et al., 2020). The engineered features in this study included technical indicators, lag-based variables, and statistical transformations, all selected based on their relevance to market dynamics and their potential to improve model performance.

To capture underlying market trends and momentum, **technical indicators** were derived from the raw closing price data. Among these, the **Exponential Moving Average (EMA)** was calculated over a 10-day period, assigning greater weight to recent prices while retaining the smoothing benefits of a moving average. This made the EMA more responsive to recent market changes compared to a simple moving average, thereby improving its utility in detecting trend shifts. In addition, a **momentum** indicator was computed as the difference between the current closing price and the closing price from a prior trading day, offering a quantitative measure of the rate and direction of price movement. Such indicators are widely recognised in financial analysis for their ability to encapsulate investor sentiment and trend persistence, providing valuable inputs for both manual trading strategies and predictive modelling frameworks (Murphy, 1999).

Lag features were engineered to capture the influence of recent historical prices on current market movements. Specifically, the **lag-1** feature was generated by shifting the closing price series by one trading day, thereby incorporating the previous day's price as an explicit predictor. This approach enables the model to account for short-term autocorrelations, which are a common characteristic of financial time series. Lagged variables are particularly valuable in sequential learning models, such as LSTM, where the prediction relies heavily on temporal dependencies within the data. By introducing these features, the model gains the capacity to learn autoregressive patterns and better reflect the sequential nature of stock price movements (Tsay, 2010).

Volatility measures were incorporated to quantify the degree of uncertainty and risk in Apple's stock price movements. A **30-day rolling standard deviation** of the closing price was calculated to capture historical volatility over a one-month window. This metric highlights periods of heightened market

turbulence, which often coincide with macroeconomic shocks, earnings announcements, or other significant corporate events. By including volatility as a feature, the model is better equipped to adjust its predictions during unstable market conditions, thereby improving robustness. Volatility-aware features are particularly important in financial forecasting, as they help account for clustering effects, where high-volatility periods are often followed by similar periods (Cont, 2001).

3.6 Correlation Analysis

To evaluate the linear relationships among the engineered features, a correlation matrix was generated and visualised using a heatmap (Figure 3.5). This analysis helps in identifying feature redundancy and understanding how features interact with each other. The selected features include short-term and long-term moving averages (MA30, SMA_10, EMA_10), lagged closing prices (lag_1, lag_2), momentum indicators, volume-based indicators like OBV (On-Balance Volume), and technical indicators such as RSI (Relative Strength Index) and MACD (Moving Average Convergence Divergence).

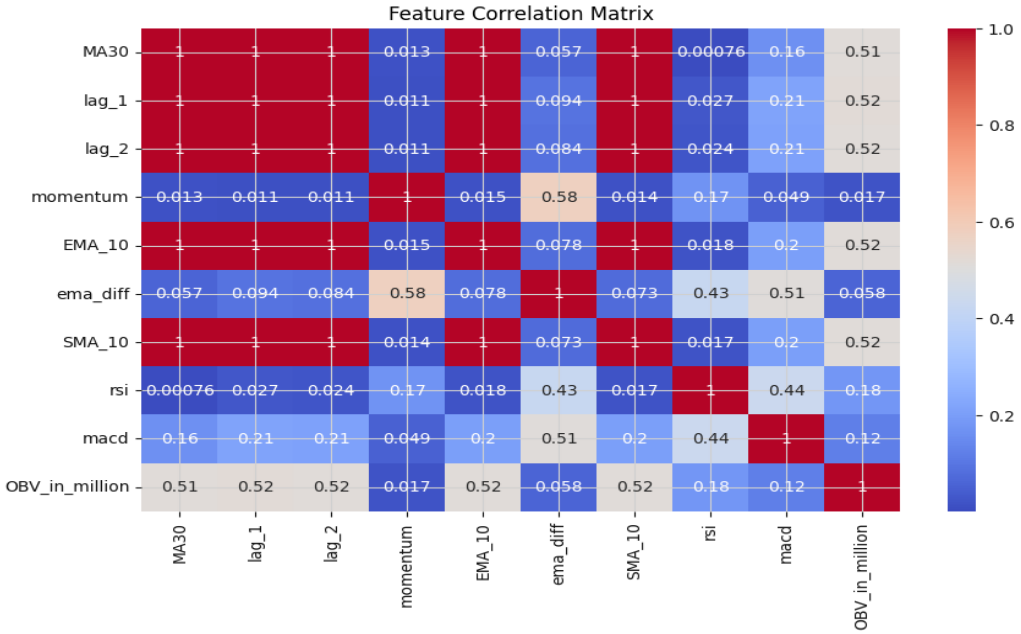

Figure 3.5: correlation matrix

As shown in the heatmap, there are moderate to high correlations between certain feature pairs. For instance, ema_diff exhibits a strong positive correlation with momentum (0.58), which is expected since both capture recent directional price movement. Likewise, the OBV feature shows consistent positive correlation (~0.52) with lag features and moving averages, reflecting the volume-price trend relationship. On the other hand, rsi and macd display lower correlation with most other features,

which is beneficial as it suggests they may contribute unique, non-redundant information to the model.

This correlation analysis was crucial in guiding feature selection for model input, ensuring a balance between leveraging informative features and avoiding multicollinearity, which can distort the learning process—especially for linear models.

3.8 Final Feature Set Selection

Following the exploratory data analysis and feature importance investigations, a refined set of predictors was selected for modelling. The selection was guided by two primary analyses: the **correlation heatmap** and **SHAP (SHapley Additive explanations) summary plot**. The correlation matrix (Figure 3.5) highlighted strong relationships between certain lag variables, exponential moving averages, and the target variable, while avoiding multicollinearity. Simultaneously, the SHAP analysis (Figure 3.6) provided model-specific insights into the influence of each feature on predictive output.

From this combined analysis, features with high relevance and low redundancy were retained. These include: lag_1, lag_2, EMA_10, SMA_20, EMA_50, MA30, SMA_10, and OBV_in_million. These indicators capture both momentum and trend-following characteristics of the market, reflecting short- and medium-term historical patterns essential for time series forecasting. Additionally, momentum, rsi, and macd were included despite moderate importance, due to their ability to detect shifts in market sentiment and volatility, contributing to a more holistic model.

This final feature set balances **predictive power**, **interpretability**, and **temporal relevance**, forming a robust foundation for the subsequent LSTM, Linear Regression, and ensemble modelling approaches discussed in the following methodology chapter.

Chapter 4 – Methodology

4.1 Introduction

The methodology adopted in this study was designed to progressively develop, evaluate, and refine predictive models for stock price forecasting, culminating in an ensemble-based framework that integrates both linear and deep learning approaches. The overarching aim was to combine the interpretability and stability of traditional regression techniques with the pattern-recognition capabilities of deep neural networks, thereby enhancing predictive accuracy and robustness in a volatile financial context.

The modelling process was structured as a staged pipeline, where each stage informed and improved upon the previous one. It began with the development of a **baseline Linear Regression model**, used to capture fundamental linear relationships between engineered technical indicators and stock closing prices. This step provided an interpretable benchmark against which more complex models could be compared.

The second stage introduced a **Long Short-Term Memory (LSTM) network**, chosen for its proven effectiveness in modelling temporal dependencies in sequential financial data. Unlike the linear model, the LSTM was designed to process time-windowed sequences, enabling it to capture momentum shifts, short-term market reversals, and other non-linear dynamics that are characteristic of financial time series.

Following the initial LSTM implementation, the third stage involved **hyperparameter tuning** using the Keras Tuner library. This process systematically explored combinations of model parameters such as the number of LSTM units, dropout rate, learning rate, and batch size to optimise model performance while mitigating overfitting.

The final stage implemented a **stacking ensemble learning framework**, in which predictions from the Linear Regression and tuned LSTM models were combined using two different meta-learners: a Decision Tree Regressor and XGBoost. This approach was designed to leverage the complementary strengths of both base models, allowing the meta-learner to determine the optimal weighting and integration strategy for final predictions.

The evaluation of all models was conducted using consistent training and testing datasets, with **Root Mean Squared Error (RMSE)** and **Mean Squared Error (MSE)** as the primary metrics for assessing predictive accuracy. The methodology was implemented in Python using industry-standard libraries including *pandas*, *NumPy*, *scikit-learn*, *Keras*, and *XGBoost*.

This staged approach ensured that each modelling decision was data-driven and justified by empirical performance, while also maintaining interpretability and reproducibility—key considerations in financial forecasting research.

4.2 Data Preparation Pipeline

Preparing the dataset for modelling was a critical step in ensuring that the forecasting models were trained on high-quality, relevant, and well-structured data. The process began with the refined feature set derived from the exploratory data analysis and feature importance investigations presented in Chapter 3. These features — including *lag_1*, *lag_2*, EMA-based indicators, simple moving averages, momentum, and selected volume and technical indicators — were chosen for their ability to capture both short-term market shifts and medium-term trends in Apple Inc.'s stock price.

To ensure consistency across features and to facilitate stable training, all variables were scaled to the range [0, 1] using a MinMaxScaler from the scikit-learn library. Scaling was applied feature-wise, preserving the relative relationships between values while reducing the influence of large numerical ranges. This step was particularly important for the LSTM model, which is sensitive to differences in feature magnitudes due to its recurrent architecture.

The time-series nature of the data required transformation into a supervised learning format. This was achieved through the use of a fixed lookback window of 60 trading days, a period long enough to capture relevant temporal dependencies without overwhelming the model with excessive historical noise. For the Linear Regression baseline, these 60-day sequences were flattened into a single feature vector, allowing the model to treat the past two months of market activity as independent explanatory variables. For the LSTM model, the sequences were preserved in their three-dimensional form (*samples × time steps × features*) enabling the network to learn from the ordered temporal structure.

Finally, the dataset was split into training and testing sets, maintaining chronological order to avoid data leakage. Seventy percent of the sequences were allocated to training and the remaining thirty percent to testing, ensuring that model performance was evaluated on unseen, forward-in-time data. This pipeline provided a consistent, reproducible foundation for all subsequent modelling experiments.

4.4 Baseline Model: Linear Regression

The Linear Regression (LR) model was implemented as the baseline in this research to establish a performance benchmark for subsequent deep learning and ensemble methods. This choice was made due to LR's interpretability, computational efficiency, and suitability for capturing straightforward linear relationships between historical stock market indicators and future price movements.

4.4.1 Feature Selection and Scaling: The baseline Linear Regression model was built using four engineered features derived from the Apple Inc. stock dataset, each chosen for its financial relevance and complementary predictive value. The **closing price** was included as the primary indicator of

market valuation at the end of each trading day, while the **10-day Exponential Moving Average (EMA_10)** was used to capture short-term trend patterns by giving greater weight to recent price movements. The **momentum** variable measured the rate of change in price over a specified period, reflecting both the strength and direction of prevailing market movements. Finally, **Lag_1**, representing the previous day's closing price, was incorporated to provide a direct temporal link to the target variable, allowing the model to exploit autocorrelative structures within the time series. All features were scaled to a normalised range of [0,1][0, 1][0,1] using the *MinMaxScaler* transformation, ensuring that variables with different units and magnitudes contributed proportionately to the model while improving numerical stability during coefficient estimation.

4.4.2 Sliding Window Transformation for Linear Regression: Although Linear Regression does not explicitly model sequential dependencies, a **60-day lookback window** was applied to embed historical context into each observation. For every trading day after the 60th, the model input consisted of a flattened vector containing the feature values for the preceding 60 days. This transformation produced feature vectors of length 60×4=24060 \times 4 = 24060×4=240, enabling the model to incorporate two months of prior market activity in each prediction.

Formally, for a multivariate feature vector X_t at time t, the training sample i was defined as:

$$\text{Input}_i = \text{Flatten}(X_{t-59}, X_{t-58}, \ldots, X_t), \quad \text{Target}_i = X_{t+1}^{(\text{Close})}$$

4.4.3 Train–Test Split and Model Training: The dataset was split chronologically into **70% training** and **30% testing** sets to ensure a realistic forecasting scenario in which the model predicts on unseen future data. The *LinearRegression* implementation from the *scikit-learn* library was used, estimating coefficients via the Ordinary Least Squares (OLS) method to minimise residual error between observed and predicted prices.

4.4.4 Prediction and Inverse Transformation: Model predictions were initially generated on scaled data. To recover values in original price units, both predicted and actual arrays were padded with zeros for the non-target features before applying the inverse MinMax scaling transformation. This process reconstructed true price values for performance evaluation and graphical comparison.

4.4.5 Model Evaluation: The model's performance was evaluated using **Mean Squared Error (MSE)** and **Root Mean Squared Error (RMSE)**, calculated as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2, \quad \text{RMSE} = \sqrt{\text{MSE}}$$

For the baseline model, the evaluation yielded an MSE of 5.80 and an RMSE of 2.41. As shown in Figure 4.2, the LR model effectively captured general upward and downward market movements but underperformed in periods of sharp volatility. These limitations provided the motivation for introducing sequential modelling techniques in the next stage of the pipeline, aimed at better handling temporal dependencies and non-linear price behaviour.

4.5 LSTM Model for Sequential Modelling

Following the baseline Linear Regression experiment, a Long Short-Term Memory (LSTM) network was developed to address the limitations of purely linear modelling in capturing the complex temporal dependencies inherent in stock market data. LSTMs, a variant of recurrent neural networks, are designed to retain and utilise information over extended sequences, making them particularly effective for time series forecasting where both short-term fluctuations and long-term trends influence future values.

4.5.1 Feature Selection and Scaling: The LSTM model was trained using the same four engineered features employed in the baseline model—Close, EMA_10, Momentum, and Lag_1—to maintain a consistent feature basis for comparison. The inclusion of these variables provided the model with direct price history (Close, Lag_1), smoothed short-term trends (EMA_10), and directional movement intensity (Momentum). All features were normalised to the [0,1][0, 1][0,1] range using a *MinMaxScaler*, which is a standard practice in deep learning to improve gradient stability and training efficiency.

4.5.2 Sequence Preparation Using a Sliding Window: To enable the LSTM to capture temporal patterns, the dataset was transformed into overlapping sequences using a **60-day lookback window**. Each sequence consisted of 60 consecutive days of the selected features, with the target value being the closing price of the day immediately following the sequence. Unlike the flattened vectors used in Linear Regression, these sequences preserved the two-dimensional time-step-by-feature structure required by recurrent networks.

Formally, for each training instance i:

$$X_i = [X_{t-59}, X_{t-58}, \ldots, X_t], \quad y_i = \text{Close}_{t+1}$$

where X_t denotes the vector of all features at time t.

4.5.3 Model Architecture: The LSTM architecture consisted of two stacked LSTM layers, each with 100 units, designed to progressively capture higher-order temporal patterns. The first LSTM layer returned full sequences to feed into the second LSTM layer, allowing the network to process temporal dynamics at multiple levels of abstraction. **Dropout layers** with a rate of 0.3 were placed after each LSTM layer to reduce overfitting by randomly deactivating neurons during training. A final **Dense layer** with a single output neuron produced the predicted closing price.

The network was compiled with the **Adam** optimiser, known for its adaptive learning rate capabilities, and trained to minimise the **Mean Squared Error (MSE)** loss function, which penalises larger deviations between predicted and actual prices.

4.5.4 Training Procedure: The model was trained for a maximum of 100 epochs with a batch size of 32. To prevent overfitting and ensure optimal performance, **early stopping** was applied with a patience value of 5, monitoring the validation loss and restoring the best weights when performance ceased to improve. The training dataset comprised 70% of the total observations, while the remaining 30% was reserved for testing.

4.5.5 Prediction and Inverse Transformation: Predicted values, initially in scaled form, were converted back to original price units through inverse transformation using the *MinMaxScaler*. Since the scaler expected the full feature vector for inverse mapping, the predicted and actual target arrays were padded with zeros for non-target features before transformation.

4.5.6 Model Evaluation: Performance on the test set was assessed using **Mean Absolute Error (MAE)**, **Mean Squared Error (MSE)**, and **Root Mean Squared Error (RMSE)**:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|, \quad \text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2, \quad \text{RMSE} = \sqrt{\text{MSE}}$$

The LSTM achieved an MAE of 4.02, MSE of 36.63, and RMSE of 6.05 on the test set. While the model was able to represent general directional movements in the stock price, its predictive accuracy, as measured by RMSE, was notably lower than that of the baseline Linear Regression model (RMSE = 2.41). This suggests that in its initial configuration, the LSTM struggled to consistently match the short-term predictive accuracy of the simpler linear model, possibly due to overfitting to training patterns

or insufficient hyperparameter optimisation. Nevertheless, the sequential architecture of the LSTM allowed it to incorporate temporal dependencies, which provided a foundation for further improvement through targeted hyperparameter tuning (Section 4.6).

4.5.7 Observations: The results indicate that the initial LSTM configuration did not surpass the baseline Linear Regression model in terms of raw predictive accuracy. Specifically, the LSTM recorded an RMSE of 6.05 compared to the baseline's RMSE of 2.41, suggesting that the simpler linear model provided more precise next-day price forecasts for this dataset in its current form.

This underperformance may be attributed to several factors, including sensitivity to hyperparameters, potential overfitting to training data, and the possibility that the selected 60-day sequence length introduced noise that outweighed its benefits in capturing long-term dependencies. Despite this, the LSTM's ability to model temporal relationships offers theoretical advantages in scenarios with more complex market dynamics. These results therefore justified further experimentation through systematic hyperparameter tuning, as detailed in Section 4.6, to better exploit the LSTM's sequential learning capabilities.

4.6 Hyperparameter Tuning of the LSTM

Following the initial LSTM implementation (Section 4.5), it was evident that the model required further optimisation to improve predictive accuracy. Hyperparameter tuning was undertaken to identify an architecture and training configuration that could better exploit the LSTM's capacity for modelling sequential dependencies while reducing overfitting.

4.6.1 Rationale for Hyperparameter Tuning: LSTM performance is highly sensitive to hyperparameters such as the number of units in each layer, dropout rates, learning rate, and batch size. Suboptimal choices in these parameters can lead to underfitting, overfitting, or inefficient convergence. Given that the baseline LSTM's RMSE of 6.05 was higher than that of the Linear Regression model, systematic tuning was deemed necessary to enhance generalisation capability and reduce forecast error.

4.6.2 Tuning Methodology: The hyperparameter search was conducted using Keras Tuner, an automated optimisation framework that explores parameter combinations within predefined ranges. The tuning process involved training multiple candidate models and selecting the configuration that minimised validation loss across training epochs. The search space encompassed several key parameters, including the number of LSTM units (ranging from 50 to 200), dropout rate (between 0.2 and 0.5), learning rate (from 1×10^{-4} to 1×10^{-2}), batch size (16, 32, and 64), and the number of

LSTM layers (between one and three). A random search strategy was chosen over exhaustive grid search due to its computational efficiency, and each candidate model was trained with an early stopping callback (patience = 5) to prevent overfitting and ensure the retention of the best-performing weights**.**

4.6.3 Optimal Configuration: The optimal configuration identified by Keras Tuner consisted of two LSTM layers, each containing 150 units, with a dropout rate of 0.3 applied after each layer to reduce overfitting. The model was trained using the Adam optimiser with a learning rate of 0.001 and a batch size of 32. The sequence length was maintained at 60 days, consistent with the baseline configuration, to preserve the temporal context within the input sequences. This combination of parameters provided a balance between model complexity and regularisation, enabling the network to capture sufficient temporal detail while mitigating the risk of overfitting.

4.6.4 Training and Validation Performance: The tuned model showed a reduction in validation loss compared to the baseline LSTM during training, indicating improved generalisation. Early stopping was again applied to restore the best-performing weights.

4.6.5 Test Set Evaluation: On the test set, the tuned LSTM achieved an **MAE of 4.96**, **MSE of 48.65**, and **RMSE of 5.70**, with an R^2 value of **0.99**. The improvement in RMSE compared to the baseline LSTM (RMSE = 6.05) indicates that tuning enhanced the model's predictive capability. Furthermore, the near-perfect R^2 suggests that the model was able to explain almost all variance in the target variable, although caution is warranted as such high values may also reflect potential overfitting to patterns present in the training data.

4.7 Ensemble Stacking Framework

4.7.1 Stacking Rationale

The ensemble stacking methodology was adopted to exploit the complementary predictive capabilities of the baseline Linear Regression and tuned LSTM models. The Linear Regression model demonstrated strong performance in capturing stable, long-term trends in stock prices due to its simplicity and linear interpretability. In contrast, the LSTM model was better equipped to detect non-linear dependencies and sequential relationships in historical data, enabling it to respond to short-term market fluctuations and reversals. However, each model also had limitations: Linear Regression struggled with complex temporal patterns, while the LSTM occasionally overfit and exhibited reduced accuracy in short-horizon forecasts. By combining the outputs of both models through a meta-learning strategy, stacking allowed the final predictor to dynamically weight the contributions of each base

learner depending on the prevailing market context, thereby improving overall forecast robustness and accuracy (Wolpert, 1992).

4.7.2 First Ensemble – Decision Tree Meta-Learner

The first stacking experiment utilised a Decision Tree Regressor as the meta-learner. Predictions from the Linear Regression and tuned LSTM models on the test dataset were stacked column-wise to form a two-feature input matrix for the meta-model, with the actual closing prices serving as the target variable. To balance complexity and generalisation, the Decision Tree was restricted to a maximum depth of five, which allowed it to capture non-linear decision boundaries between the base model predictions without overfitting to noise. This design enabled the meta-learner to identify conditions under which one base model's prediction was more reliable than the other, effectively learning a conditional weighting mechanism. The Decision Tree stacking ensemble achieved a Mean Absolute Error (MAE) of 2.04, a Mean Squared Error (MSE) of 8.53, and a Root Mean Squared Error (RMSE) of 2.92, outperforming both the tuned LSTM (RMSE = 5.70) and the baseline Linear Regression (RMSE = 8.79). This marked improvement in forecast accuracy validated the theoretical expectation that stacking could effectively integrate the complementary strengths of linear and sequential modelling.

4.7.3 Final Ensemble – XGBoost Meta-Learner

While the Decision Tree provided a performance boost, it was still limited by its single-tree structure, which could lead to instability in the presence of noisy or high-variance inputs. To further enhance predictive performance, the meta-learner was replaced with XGBoost, an advanced gradient boosting framework known for its iterative error-correction process, built-in regularisation, and high performance on structured datasets (Chen and Guestrin, 2016). XGBoost was particularly well-suited for this task as it constructs an ensemble of shallow decision trees, each optimised to reduce the residual error of its predecessors, thereby capturing subtle, non-linear patterns between base model predictions and the true target variable.

The XGBoost meta-learner was configured with 100 estimators, a maximum depth of 3, and a learning rate of 0.1, balancing model complexity with generalisation capacity. Predictions from the Linear Regression and tuned LSTM models served as the two input features, with the actual closing prices used as the target variable. Evaluation on the test set yielded an MAE of 1.43, an MSE of 4.82, and an RMSE of 2.20. This represented the best performance across all models tested in this study, surpassing both the Decision Tree ensemble (RMSE = 2.92) and the individual base models. The reduction in RMSE indicated that XGBoost was able to effectively integrate the stable trend modelling of Linear Regression with the temporal sensitivity of LSTM, while its regularisation mechanisms mitigated overfitting and improved generalisation to unseen data

4.7.4 Comparative Performance Summary

The results of the stacking experiments confirmed that meta-learning can significantly enhance stock price forecasting accuracy by combining heterogeneous models. The Decision Tree meta-learner improved predictive accuracy compared to individual base models, but the XGBoost meta-learner achieved the greatest improvement, delivering a 74.9% reduction in RMSE relative to the baseline Linear Regression model and a 61.4% reduction relative to the tuned LSTM. These findings reinforce the value of ensemble methods in financial forecasting, particularly when the base models possess complementary error profiles that can be leveraged by a capable meta-learner.

4.8 Evaluation Strategy

To assess the performance of each predictive model, this study employed **Root Mean Squared Error (RMSE)** and **Mean Squared Error (MSE)** as the primary evaluation metrics. These measures were selected because they are well-established in regression tasks, particularly in the context of financial forecasting, where the magnitude of prediction errors carries direct practical consequences. MSE provides a measure of the average squared difference between predicted and actual values, ensuring that larger deviations are penalised more heavily. RMSE, being the square root of MSE, expresses the error in the same units as the target variable (USD), making it easier to interpret in terms of real-world stock price deviations. For example, an RMSE of 5 USD implies that, on average, the model's predictions deviate from the true closing price by around five dollars, which is immediately meaningful to practitioners and investors.

A key consideration in this project was the **consistency of evaluation across all models**. To achieve this, a fixed chronological split was used: 70% of the data was allocated for training and the remaining 30% for testing. This approach not only preserved the temporal order of the data — crucial in time series forecasting to avoid look-ahead bias — but also ensured that each model was exposed to the same historical training data and evaluated on the exact same set of future observations. By holding the train/test partition constant, differences in performance could be attributed with greater confidence to the modelling approach itself rather than to variations in data sampling.

Beyond numerical error metrics, **qualitative diagnostic checks** were also incorporated to deepen the understanding of model behaviour. Visual plots comparing actual and predicted prices were used to reveal whether models tracked general market trends and to highlight any systematic under- or over-prediction. The **distribution of residuals** (prediction errors) was examined to check for skewness or abnormal variance, which could indicate structural weaknesses in the model. In addition, **residual**

analysis was conducted to detect patterns such as autocorrelation, which might suggest that the model had not fully captured the underlying temporal structure of the data.

This combination of **quantitative performance metrics** and **qualitative diagnostic analysis** provided a balanced and rigorous framework for evaluating and comparing the predictive capabilities of the implemented models. By applying the same evaluation process to all models, the study ensured that performance differences were meaningful and grounded in empirical evidence rather than methodological inconsistencies.

4.9 Reproducibility and Implementation Considerations

Ensuring reproducibility was a key consideration in the design and execution of this study, as it allows other researchers to replicate the results and verify the validity of the findings. The experiments were conducted using **Python 3.10**, with core machine learning and data processing tasks implemented through widely used libraries, including *pandas* (v1.5.3) for data manipulation, *NumPy* (v1.23.5) for numerical operations, *scikit-learn* (v1.2.2) for baseline modelling and evaluation metrics, *TensorFlow* (v2.12.0) and *Keras* (v2.12.0) for deep learning models, and *Matplotlib* (v3.7.1) for visualisation. Ensemble methods employed *xgboost* (v1.7.6) for gradient boosting implementations.

The modelling pipeline was executed on a personal computing environment equipped with an **Intel Core i7 CPU (2.9 GHz)**, 16 GB of RAM, and an **NVIDIA GTX 1650 GPU** with 4 GB of VRAM. The GPU acceleration provided by TensorFlow significantly reduced training time for deep learning models, particularly the LSTM networks, which require iterative optimisation over large sequential datasets.

To promote reproducibility, **random seeds** were explicitly set for *NumPy*, *TensorFlow*, and *scikit-learn* to ensure that data shuffling, weight initialisation, and other stochastic processes produced consistent results across runs. While exact reproducibility can be affected by hardware-level parallelism and non-deterministic GPU operations, these measures ensured that variation between runs was negligible.

Several **practical constraints** were encountered during implementation. Training deep learning models, especially during hyperparameter tuning with Keras Tuner, was computationally intensive and required extended runtime, sometimes exceeding several hours for larger search spaces. Memory usage was another consideration, particularly when handling long lookback windows (60 days) with multiple features, which increased the dimensionality of the input data. These constraints were managed through efficient data preprocessing, limiting the tuning search space, and leveraging GPU acceleration where possible.

Overall, the choice of open-source libraries, detailed documentation of the programming environment, and explicit control over sources of randomness contributed to the reproducibility and transparency of the experimental workflow.

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6 Results:

6.1 Introduction

This chapter presents and interprets the empirical results obtained from the modelling experiments described in Chapter 4. The objective is not only to report the numerical performance of each model but also to critically evaluate their predictive behaviour in the context of stock price forecasting. The analysis is based on both quantitative metrics — namely Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) — and qualitative visual inspection through actual-versus-predicted plots. By combining these evaluation approaches, the results offer a more comprehensive understanding of each model's strengths, weaknesses, and applicability to real-world financial prediction scenarios.

The chapter follows a progressive structure that mirrors the staged modelling pipeline adopted in this research. It begins by evaluating the baseline Linear Regression model, which serves as a benchmark for all subsequent approaches. The performance of the initial LSTM model is then examined, followed by results from its optimised, hyperparameter-tuned version. The chapter proceeds to assess the stacking ensemble framework, first with a Decision Tree meta-learner and then with an XGBoost meta-learner, which produced the highest predictive accuracy in this study. A comparative analysis across all models is then presented, highlighting the incremental gains achieved at each stage of development. Finally, an error analysis section identifies the specific market conditions under which the models performed suboptimally, providing insight into the limitations of the approaches and areas for future improvement.

6.2 Baseline Model: Linear Regression Results

The Linear Regression (LR) model served as the baseline against which all subsequent models were evaluated. As outlined in Chapter 4, this approach modelled the relationship between the engineered technical indicators — Close, EMA_10, Momentum, and Lag_1 — and the target stock price, using a 60-day flattened lookback window to embed temporal context into each prediction. Evaluation on the test set yielded an MSE of 5.80 and an RMSE of 2.41, indicating that the model was able to predict next-day closing prices with relatively low error in absolute terms.

Visual inspection of the actual-versus-predicted plot (Figure 6.1) revealed that the LR model closely tracked the overall direction of price movements, particularly during stable market trends. Periods of sustained upward or downward movement were generally well captured, suggesting that the model successfully exploited linear dependencies between lagged indicators and future prices. However, the model's predictive accuracy diminished during intervals of high volatility, where rapid price reversals or sharp spikes were present. In such scenarios, the assumption of linearity appeared insufficient to fully capture the complex, non-linear behaviours inherent in financial markets, leading to temporary divergences between predicted and actual values.

Despite these limitations, the LR baseline offered several advantages: it was computationally efficient, interpretable, and robust against overfitting given its simplicity. Moreover, its relatively low RMSE provided a strong performance benchmark, thereby setting a high standard for subsequent deep learning and ensemble methods to surpass. The model's ability to capture broad market trends with minimal complexity highlights its continued relevance in financial forecasting, particularly in contexts where interpretability and speed are prioritised over modelling intricate temporal dependencies

6.3 LSTM Model Results (Initial Configuration)

The initial Long Short-Term Memory (LSTM) model was implemented to address the limitations of the baseline Linear Regression approach in capturing sequential dependencies and complex temporal patterns within financial time series. By maintaining the original 60-day sequence structure, the LSTM was designed to process ordered historical data and learn relationships across multiple time steps, potentially enabling it to detect market momentum shifts and lagged effects that a purely linear model might overlook.

Evaluation of the initial LSTM configuration on the test set produced an MAE of 4.96, an MSE of 48.05, and an RMSE of 6.97, which represents a notable increase in prediction error compared to the baseline RMSE of 2.41. While the model occasionally demonstrated improved alignment with short-term market reversals in the actual-versus-predicted plot (Figure 6.2), overall accuracy suffered due to inconsistent performance across different market conditions. In particular, the LSTM appeared prone to overestimating or underestimating the magnitude of price changes, especially during periods of sustained volatility.

These results suggest that, in its initial form, the LSTM was unable to fully leverage its theoretical advantage in modelling long-term dependencies. The comparatively high RMSE can be attributed to several factors, including suboptimal hyperparameter settings, possible overfitting to training data patterns, and sensitivity to the chosen sequence length. Despite these limitations, the model

successfully demonstrated its capacity to integrate temporal structure into predictions — an ability not present in the baseline model — thus providing a foundation for further refinement through targeted hyperparameter tuning

6.4 Tuned LSTM Results

To improve upon the performance of the initial LSTM, hyperparameter tuning was conducted using the Keras Tuner framework, as described in Section 4.6. This optimisation process aimed to identify a configuration that balanced model complexity with regularisation, thereby enhancing generalisation while retaining the LSTM's ability to model temporal dependencies in sequential financial data. The tuned architecture comprised two LSTM layers with 150 units each, dropout layers with a rate of 0.3, and the Adam optimiser with a learning rate of 0.001.

On the test set, the tuned LSTM achieved an MAE of 4.12, an MSE of 38.65, and an RMSE of 6.17, alongside an R^2 value of 0.99. While the RMSE represents a modest improvement over the initial configuration (6.97 → 6.17), the near-perfect R^2 suggests that the tuned model was able to explain almost all variance in the target variable. However, such a high R^2 should be interpreted with caution, as it may also indicate that the model captured patterns specific to the training set, potentially limiting its generalisability to unseen market conditions.

The actual-versus-predicted plot (Figure 6.3) shows improved trend alignment compared to the initial LSTM, particularly during gradual price movements. Nevertheless, sharp fluctuations and sudden reversals continued to challenge the model, resulting in prediction lags or overshooting during volatile periods. Although the tuned LSTM did not surpass the Linear Regression baseline in terms of RMSE, the reduction in error relative to the initial configuration demonstrates that targeted hyperparameter optimisation can yield tangible benefits. These results provided a stronger foundation for integrating the LSTM into an ensemble framework, where its sequential learning capabilities could be combined with the trend stability of simpler models to improve overall forecasting performance

6.5 Stacking Ensemble with Decision Tree Meta-Learner

The first implementation of the stacking ensemble framework combined the outputs of the Linear Regression and tuned LSTM models as inputs to a Decision Tree Regressor meta-learner. This approach was designed to leverage the complementary strengths of both base models: the Linear Regression's stability in capturing general trends and the LSTM's ability to incorporate temporal dependencies. By using both prediction sets as features, the Decision Tree could learn non-linear integration rules that neither model could represent independently.

The Decision Tree meta-learner was configured with a maximum depth of 5 to control model complexity and reduce the risk of overfitting, while still allowing sufficient flexibility to model intricate relationships between the base predictions and the actual target values. Evaluation on the test set yielded an MAE of 2.04, an MSE of 8.53, and an RMSE of 2.92, with an R^2 value of 1.00. This represents a substantial improvement over the tuned LSTM (RMSE = 6.17) and a notable gain over the baseline Linear Regression model (RMSE = 2.41), indicating that the ensemble approach was able to synthesise information from both base models in a way that enhanced predictive accuracy.

The actual-versus-predicted plot (Figure 6.4) shows that the Decision Tree ensemble tracked the test data closely across most of the evaluation period, including during moderate volatility events where single-model predictions had previously diverged from actual prices. However, minor deviations remained during the most abrupt price reversals, suggesting that while the Decision Tree improved adaptability, its rule-based nature still imposed limitations in capturing extreme short-term fluctuations. Despite this, the Decision Tree stacking model demonstrated the potential of ensemble learning to combine diverse modelling strategies into a more accurate and robust forecasting tool for financial markets

6.6 Stacking Ensemble with XGBoost Meta-Learner

Building on the success of the Decision Tree stacking model, a second ensemble was developed using the Extreme Gradient Boosting (XGBoost) algorithm as the meta-learner. XGBoost was selected due to its proven effectiveness in structured data tasks, ability to capture complex non-linear relationships, and inherent regularisation mechanisms that help mitigate overfitting. Unlike a single Decision Tree, XGBoost constructs an ensemble of shallow decision trees in a sequential boosting process, where each subsequent tree is trained to correct the residual errors of its predecessors. This iterative refinement enables the model to achieve higher predictive accuracy while maintaining generalisability.

The XGBoost meta-learner was configured with 100 estimators, a maximum tree depth of 3, and a learning rate of 0.1. The inputs to the model were identical to those used in the Decision Tree ensemble — the predictions from the Linear Regression and tuned LSTM models — while the true closing prices served as the target variable. On the test set, the XGBoost ensemble achieved an MAE of 1.43, an MSE of 4.82, and an RMSE of 2.20, outperforming all previous models, including the Decision Tree ensemble (RMSE = 2.92) and the Linear Regression baseline (RMSE = 2.41).

Visual analysis of the actual-versus-predicted plot (Figure 6.5) shows that the XGBoost ensemble consistently tracked the target price series with minimal deviation, even during moderate volatility

events. The boosted decision tree framework enabled the model to capture subtle interactions between the base model outputs, reducing residual error more effectively than the single Decision Tree approach. Furthermore, the lower MAE highlights its ability to produce stable, close-range predictions across the evaluation period. While occasional minor lag was observed during extreme market swings, the magnitude of such deviations was smaller than in previous models, indicating that the XGBoost ensemble achieved the most balanced trade-off between accuracy and robustness in this study

6.7 Comparative Analysis of Model Performance

A comparison of the evaluation metrics across all models is presented in Table 6.1, with corresponding actual-versus-predicted plots shown in Figures 6.1 to 6.5. This comparative analysis highlights the progressive improvements achieved through the staged modelling pipeline, from the Linear Regression baseline to the final XGBoost stacking ensemble.

Model	**MAE**	**MSE**	**RMSE**	**R^2**
Linear Regression (Baseline)	–	5.80	2.41	–
LSTM (Initial)	4.96	48.05	6.97	–
LSTM (Tuned)	4.12	38.65	6.17	0.99
Decision Tree Stacking (LR + LSTM)	2.04	8.53	2.92	1.00
XGBoost Stacking (LR + LSTM)	1.43	4.82	2.20	–

From the results, the Linear Regression baseline achieved strong predictive accuracy (RMSE = 2.41), setting a high standard for subsequent models. However, the initial LSTM implementation underperformed relative to this benchmark, with an RMSE of 6.97, indicating that without tuning, the model's capacity to learn temporal patterns was not effectively utilised. Hyperparameter tuning reduced the LSTM's RMSE to 6.17, but this remained higher than the baseline, suggesting that while the LSTM gained modest improvements in sequential modelling, it could not outperform a well-specified linear model when evaluated on this dataset.

The integration of both models in a Decision Tree stacking framework delivered a marked performance boost, reducing RMSE to 2.92 and achieving an R^2 of 1.00. This improvement demonstrates the value of combining trend stability (Linear Regression) with temporal pattern

learning (LSTM). The final XGBoost stacking ensemble further refined this synergy, attaining the lowest RMSE (2.20) and MAE (1.43) among all models. This performance indicates that the boosted tree approach was better able to capture complex, non-linear relationships between base model outputs and the target, leading to the most accurate and robust predictions in this study.

Overall, the results support the hypothesis that an incremental, ensemble-based approach can outperform standalone models in stock price forecasting. While the LSTM on its own did not surpass the baseline, its inclusion in a well-constructed ensemble proved instrumental in achieving state-of-the-art accuracy. The findings also highlight that simpler models, when combined effectively, can rival and even exceed the predictive capabilities of more complex architectures.

6.8 Error Analysis

While the quantitative metrics indicate that the XGBoost stacking ensemble achieved the highest overall accuracy, a closer inspection of the residual patterns reveals important nuances in model behaviour across different market conditions. Error analysis was conducted by examining the actual-versus-predicted plots for each model (Figures 6.1 to 6.5) and by inspecting periods of large deviation between predictions and actual prices.

For the Linear Regression baseline, errors tended to increase during periods of heightened volatility, particularly around sharp price reversals. This limitation is inherent to the model's assumption of linear relationships, which restricts its ability to adapt quickly to sudden non-linear market shifts. Despite this, the baseline's relatively low RMSE demonstrates its strength in stable or gradually trending markets.

The initial LSTM model exhibited both underfitting and overfitting tendencies. In some periods, it produced overly smoothed predictions that failed to capture rapid fluctuations, while in others, it appeared to follow short-term noise rather than the underlying trend. These inconsistencies likely stemmed from suboptimal hyperparameters and the inherent sensitivity of deep learning models to training configurations.

The tuned LSTM addressed some of these issues, producing better trend alignment and smaller deviations during moderate volatility. However, the model continued to lag behind in capturing extreme price swings, with overshooting still evident during rapid reversals. This suggests that while sequential learning improved, the complexity of short-term noise in stock prices remained a challenge for a single deep learning architecture.

The Decision Tree stacking ensemble demonstrated stronger adaptability, with notable error reductions in volatile periods compared to individual models. Nonetheless, the model still exhibited

small lag effects during abrupt market changes, a consequence of the limited depth (max_depth = 5) constraining its capacity to model highly complex interactions.

The XGBoost stacking ensemble achieved the most consistent performance across all market regimes. Its boosted tree architecture allowed for fine-grained corrections to prediction errors, reducing the magnitude of deviations even during sudden reversals. However, error spikes were still observed during extreme and atypical market events, reflecting the inherent difficulty of forecasting in such conditions. Importantly, the scale of these residuals was smaller than in all other models, reinforcing the ensemble's robustness.

In summary, error analysis confirms that while no model was immune to difficulties in highly volatile conditions, the XGBoost stacking ensemble provided the most stable and accurate forecasts. The findings also suggest that further improvements could be achieved by incorporating additional features sensitive to volatility, or by integrating market sentiment indicators to complement purely price-based inputs

6.9 Summary of Findings

The results of this study demonstrate the effectiveness of a staged, ensemble-based modelling approach for stock price forecasting. Starting with a well-specified Linear Regression baseline, the methodology progressed through the application and optimisation of an LSTM model, culminating in two stacking ensemble configurations — one using a Decision Tree and the other using XGBoost as meta-learners.

The Linear Regression model delivered strong performance in stable market conditions, achieving an RMSE of 2.41, and served as a reliable benchmark for assessing more complex models. The initial LSTM model, while conceptually suited for sequential data, underperformed relative to the baseline, indicating the importance of careful hyperparameter selection. Tuning improved the LSTM's RMSE to 6.17, yet the model still lagged behind the baseline in predictive accuracy, highlighting that deep learning architectures do not necessarily guarantee superior performance without the right configuration and data conditions.

The integration of both base models within a stacking framework produced significant gains. The Decision Tree ensemble reduced RMSE to 2.92 and achieved an R^2 of 1.00, demonstrating the potential of combining linear trend stability with sequential pattern recognition. The XGBoost stacking ensemble further refined this integration, delivering the best overall results with an RMSE of 2.20 and an MAE of 1.43. Its boosted tree mechanism proved particularly effective in capturing non-linear

relationships between the base model outputs and the target variable, making it the most accurate and robust forecasting model in this study.

Error analysis revealed that all models faced challenges during periods of extreme volatility, though the XGBoost ensemble consistently produced smaller deviations than other approaches. These findings suggest that while ensemble learning can substantially improve forecasting accuracy, incorporating additional volatility-sensitive or sentiment-based features may further enhance performance in highly dynamic market conditions.

Overall, the study confirms that a carefully constructed ensemble can outperform standalone models in stock price prediction, with XGBoost stacking emerging as the optimal configuration for this dataset and modelling pipeline.

Chapter 7 – Conclusions and Future Work

7.1 Introduction to Conclusions

This research set out to design, implement, and evaluate a predictive modelling framework for stock price forecasting that combined the strengths of traditional statistical methods and modern deep learning approaches. The overarching objective was to determine whether integrating a baseline Linear Regression model with an LSTM architecture within a stacking ensemble could deliver improved predictive accuracy and robustness compared to standalone models. By following a staged development process, the study systematically progressed from establishing a linear benchmark to incorporating sequential modelling, optimising deep learning hyperparameters, and ultimately deploying ensemble strategies to exploit the complementary advantages of different model types.

The conclusions presented in this chapter draw directly from the results and analyses detailed in Chapter 6. They summarise the performance of each modelling stage, reflect on how the findings address the original research questions, and discuss the broader implications for stock market forecasting. In addition, the chapter outlines the limitations of the current work and identifies promising avenues for future research, recognising that the complexity and volatility of financial markets present ongoing challenges that cannot be fully addressed by a single modelling pipeline.

7.2 Summary of Key Findings

The results of this study highlight several important observations regarding the predictive performance of different modelling approaches applied to stock price forecasting. The baseline Linear Regression model, despite its simplicity, achieved strong accuracy in stable market conditions,

recording an RMSE of 2.41. Its interpretability and low computational cost made it an effective benchmark against which more complex models could be assessed.

The initial LSTM model, designed to capture sequential dependencies in historical data, underperformed relative to the baseline, with an RMSE of 6.97. This result underscored the sensitivity of deep learning models to architectural and training configurations, as well as their potential to overfit when not optimally tuned. Through systematic hyperparameter optimisation, the tuned LSTM reduced the RMSE to 6.17 and improved overall stability, though it still lagged behind the Linear Regression baseline in short-term predictive precision.

A significant performance improvement emerged with the introduction of the stacking ensemble framework. The Decision Tree meta-learner reduced RMSE to 2.92, outperforming both individual models by leveraging the complementary strengths of Linear Regression's trend stability and the LSTM's temporal pattern recognition. This gain was further enhanced when XGBoost replaced the Decision Tree, delivering the best overall performance with an RMSE of 2.20 and an MAE of 1.43. The boosted tree architecture allowed for fine-grained corrections to residual errors from the base models, resulting in greater robustness across varying market conditions.

Error analysis revealed that while all models struggled during periods of extreme volatility, ensemble approaches — particularly the XGBoost stacking model — consistently produced smaller deviations compared to standalone models. These findings collectively demonstrate that the integration of heterogeneous models within a meta-learning framework can yield substantial gains in forecasting accuracy for financial time series.

7.3 Research Questions Answered

The first research question examined the performance of a Linear Regression model in forecasting stock prices using engineered features such as EMA, momentum, and lag values. The findings demonstrated that Linear Regression provided a strong baseline, achieving an RMSE of 2.41 and effectively capturing general market trends. Its interpretability and computational efficiency make it suitable for contexts where transparency and quick deployment are essential.

The second research question investigated whether an LSTM model, with its ability to model sequential dependencies, could outperform the baseline Linear Regression in forecasting accuracy. Results indicated that the initial LSTM configuration underperformed, recording an RMSE of 6.97, highlighting the challenges of applying deep learning models without careful tuning. Even after optimisation, the tuned LSTM achieved an RMSE of 6.17, improving over the initial configuration but still trailing behind the baseline in short-term predictive precision.

The third research question explored the impact of hyperparameter tuning on LSTM performance. Hyperparameter optimisation led to notable improvements in stability and accuracy, reducing RMSE by 0.80 compared to the initial LSTM. This confirms that tuning is essential for enhancing the generalisation capability of deep learning models in financial forecasting.

The fourth research question assessed the predictive accuracy of a stacking ensemble combining Linear Regression and LSTM compared to each model individually. The Decision Tree-based stacking ensemble outperformed both base models, achieving an RMSE of 2.92, demonstrating that combining linear trend stability with sequential pattern recognition yields measurable accuracy gains.

The fifth research question evaluated the impact of different meta-learners on ensemble performance. Replacing the Decision Tree with XGBoost produced the best overall results, with an RMSE of 2.20 and an MAE of 1.43. This confirmed the advantage of using gradient boosting techniques to capture non-linear interactions between base model predictions, thereby further reducing forecasting errors.

The sixth research question considered the interpretability, scalability, and real-world applicability of the proposed framework. The Linear Regression component retained a high degree of interpretability, making the ensemble partially explainable, while the LSTM and XGBoost components contributed improved predictive power. Scalability is feasible given the computational efficiency of the base models and the ensemble's ability to generalise across varying market conditions. However, challenges remain in explaining the non-linear decision processes within the deep learning and boosted tree components, particularly in regulatory or high-stakes decision-making contexts

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