Title: Predictive Analytics for financial Decision support

Student Number: 202300015

being a dissertation submitted in partial fulfilment of the requirements for the degree of

Master of

Artificial Intelligence and Data Science

in the University of Hull

by

OGUCHE BLESSING UNEKUOJO

Dedication

I am dedicating the study to God Almighty and to my family who have been there for me.

Acknowledgements

My deepest gratitude to the University of Hull, Hull library, DAIM lab for providing with resources vital to the completion of this dissertation. A big thank you to my project supervisor, Dr Julius Mboli for his guidance, insightful feedback and unwavering support during the time of this study, and to all my tutors who have taught me.

Thank you all for making this achievement possible.

Abstract

The study explores advanced machine learning and deep learning models to predict Bitcoin's price movements, addressing challenges posed by its high volatility and dynamic market behaviour. Traditional financial models often fail to capture Bitcoin's price complexities, leading to inaccurate predictions. This research evaluates models like LSTM, GRU, Bi-Directional LSTM, Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and SVR, focusing on hyper parameter tuning and ensemble methods. A key contribution is the Stacked Ensemble model, which integrates LSTM, GRU, and Bi-Directional LSTM predictions into a Linear Regression meta-model, enhancing predictive accuracy. Results show the Stacked Ensemble model outperforms individual models, achieving the highest accuracy in predicting Bitcoin prices. The study highlights the importance of hyper parameter tuning in volatile markets like cryptocurrency. This research demonstrates the effectiveness of advanced machine learning techniques in financial forecasting, offering practical insights for investors and traders. Future research should refine ensemble approaches and apply them to a broader range of financial assets to improve prediction accuracy and robustness.

Keywords: Bitcoin, Price Prediction, Volatility, Machine Learning, Deep Learning, LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), Bi-Directional LSTM, Stacked Ensemble Model, Linear Regression, Decision Tree, Random Forest, Gradient Boosting, Support Vector Regression (SVR), Hyperparameter Tuning, Cryptocurrency

Contents

List of Figures

List of Tables

1. INTRODUCTION

1.1 Background of the Study

The rise of cryptocurrencies, led by Bitcoin, has revolutionised the financial landscape, (Nakamoto, 2008). Bitcoins decentralised peer-to peer medium of transaction has brought about an alternative to traditional monetary system, thereby influencing the creation of numerous other cryptocurrencies., leading to a dynamic market characterised by significant price volatility.

Bitcoin's increasing impact on the global economy is driving financial innovation and creating new investment opportunities, hence the need for accurate price prediction.

Cryptocurrency markets are unpredictable and volatile. hence, traditional financial models struggle to capture its unique dynamics. This has led researchers to explore advanced machine learning and deep learning models in predicting cryptocurrency price movements (Nakamoto, 2008; Valencia et al., 2019).

The study "**PREDICTIVE ANALYTICS FOR FINANCIAL DECISION SUPPORT**" uses Bitcoin as a case study to explore advanced machine learning techniques for improved forecasting, aiming to enhance reliability across the cryptocurrency market.

1.2 Problem Statement

The prediction of Bitcoin prices is a complex and challenging task due to the high volatility and non-stationary nature of cryptocurrency markets (Mohammadjafari, 2024).

Traditional financial models often fall short in capturing the intricate patterns within the data, leading to inaccurate forecasts (Khan et al., 2023).

Although deep learning models like LSTM and GRU have shown promise in time series forecasting, there is a need to systematically compare these models with traditional approaches and assess their performance in predicting Bitcoin prices.

This research addresses the need for robust and dependable predictive models that can provide investors and traders with actionable insights in a volatile and rapidly evolving market.

1.3 Aims and Objectives

1.3.1 Aims

The primary aim of this study is to develop and evaluate predictive models for forecasting the price of Bitcoin using historical price and volume data. The study seeks to compare the effectiveness of different machine learning and deep learning approaches, including LSTM, GRU, and Bi-Directional LSTM, along with traditional machine learning models such as Linear Regression, Decision Tree, Random Forest, and Support Vector Regression (SVR).

1.3.2 Objectives

1. To design and implement various deep learning models (LSTM, GRU, Bi-Directional LSTM) and machine learning models (Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and SVR) for Bitcoin price prediction.
2. To evaluate and compare the performance of the different models using metrics such as RMSE, MAPE, and R^2.
3. To analyse the volatility of Bitcoin prices

1.4 Research Questions

1. Which predictive model provides the most accurate forecasts for Bitcoin prices among LSTM, GRU, Bi-Directional LSTM, and traditional machine learning models?
2. How does the performance of deep learning models compare to traditional machine learning models and Time series model in predicting Bitcoin prices?
3. What is the impact of hyperparameter tuning on the accuracy and robustness of the predictive models?
4. How does Bitcoin's price volatility influence the accuracy of the predictions?
5. Can ensemble methods improve the accuracy of Bitcoin price predictions over individual models?

1.5 Significance of the Study

This study is significant in that Bitcoin price predictions are crucial for informed financial decision-making, risk management, and advance predictive modelling. They offer valuable technological insights into applying machine learning and deep learning techniques in the highly speculative cryptocurrency market.

1.6 Scope and Limitations

Predicting Bitcoin prices using historical data faces several key challenges and limitations:

1. Bitcoin's extreme price fluctuations make it difficult to identify consistent trends, while the efficient market hypothesis suggests that all available information is already reflected in current prices, limiting predictive power.

2. Bitcoin's short market history and potential data quality issues reduce the amount of reliable data available for analysis, impacting model development.
3. Regulatory changes, technological advancements, economic conditions, and market manipulation introduce significant unpredictability, making accurate predictions challenging.
4. Overfitting and inherent model uncertainty are concerns, as even sophisticated models may not fully capture the complex, dynamic nature of the cryptocurrency market.
5. Limited computational resources may restrict the ability to perform extensive hyperparameter tuning or use more advanced models, potentially affecting accuracy.

2. LITERATURE REVIEW

Bitcoin has come a long way from being a niche digital currency to becoming a widely recognised investment asset, significantly impacting the financial landscape. It was introduced in 2008 by Satoshi Nakamoto. As this market matures, there is a growing focus on advanced predictive models to manage the complexities of cryptocurrency price movements. Studies are increasingly advocating for machine learning and deep learning techniques over traditional forecasting methods. (Nakamoto, 2008; Valencia et al., 2019; Girsang, 2023; Patel et al., 2020).

2.1 Limitations of Traditional Forecasting Methods

According to Amirzadeh *et al.* (2022), machine learning algorithms can spot patterns in financial data and make better predictions about future trends.

However, studies by Poongodi *et al.* (2020), Rathore *et al.* (2022), Guo *et al.* (2021), and Tapia and Kristjanpoller (2022) have shown that traditional time-series models like ARIMA and GARCH are not well-suited for predicting cryptocurrency prices due to their inability to capture the market's high volatility, non-stationarity, and non-linearity. To overcome these limitations, researchers have explored hybrid models, which have shown promising results in capturing the complex dynamics of cryptocurrency markets.

2.2 Effectiveness of Machine Learning and Deep Learning Models

Machine learning (ML) AND Deep learning models have shown growing effectiveness in predicting cryptocurrency prices. Valencia et al (2019) showed that combining ML with social media sentiment analysis effectively predicts price movements for cryptocurrencies. Girsang (2023) achieved superior accuracy compared to benchmark models when they integrated historical price data with social media sentiment analysis using a hybrid LSTM-GRU model.

Patel et al. (2020) proposed a stochastic neural network model based on the random walk theory, while AlMadany et al. (2024) emphasized the superiority of deep learning models over classical statistical techniques in handling the complex and volatile nature of cryptocurrency markets. Similarly, Amirshahi and Lahmiri (2023) found that hybrid models combining deep learning with GARCH-type models outperformed singular models in forecasting market volatility.

Akyildirim et al. (2021) and Chen et al. (2020) highlighted the reliability and superior accuracy of machine learning models in cryptocurrency price prediction. Zuo (2024) further emphasized the effectiveness of ML algorithms in capturing nonlinear market behaviours. Singh et al. (2022) and Jones and Demirel (2022) demonstrated the adaptability of deep learning models to changing market conditions, while Tapia and Kristjanpoller (2022) applied LSTM models alongside error analysis to predict Bitcoin volatility, finding that these hybrid models provided more accurate forecasts than traditional methods.

These findings underscore the enhanced predictive power of combining different modelling techniques to address the complexities of cryptocurrency markets.

3. METHODOLOGY

3.1 Data Collection

The dataset utilised in this study was sourced from Yahoo Finance, a well-established and reputable provider of financial data. The dataset comprises daily historical prices for Bitcoin (BTC-USD) over an extensive period, specifically from January 1, 2015, to December 31, 2023. This dataset was selected for its comprehensive coverage of Bitcoin's price movements across different market conditions.

The dataset includes the following key features, with all monetary values expressed in **U.S. dollars (USD)**:

- **Open:** The opening price of Bitcoin (in USD) for each trading day.
- **High:** The highest price reached by Bitcoin (in USD) during each trading day.
- **Low:** The lowest price observed for Bitcoin (in USD) during each trading day.
- **Close:** The closing price of Bitcoin (in USD) at the end of each trading day, which is the primary target variable for this study.
- **Volume:** The total trading volume of Bitcoin during each trading day, reflecting the amount of Bitcoin traded.

3.2 Data Preprocessing

- The dataset was checked for duplicates and missing values, no missing values were found.
- The study focused on 'Open', 'High', 'Low', 'Close', and 'Volume' features. Additional features like daily returns and rolling volatility were engineered to capture more complex patterns.
- Data was scaled using MinMaxScaler, normalizing feature values to a range between 0 and 1.

3.3 Model Development

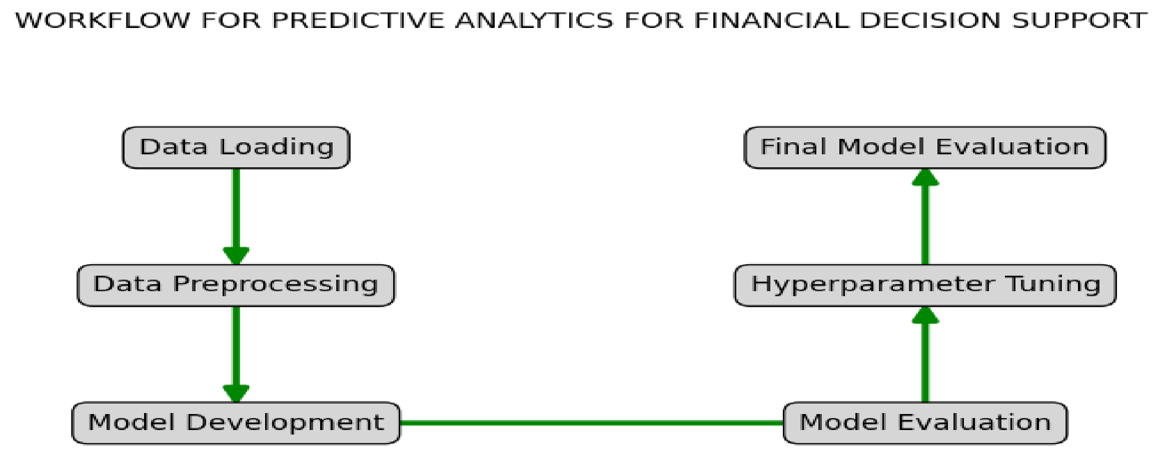


Figure 1: Model development Workflow

Figure 1 shows the workflow of this study from loading the data through final evaluation.

3.3.1 Deep Learning Models

The study used **Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bi-Directional** The LSTM model includes two LSTM layers with 50 units each, dropout layers to prevent overfitting, and a Dense layer for the predicted closing price. The GRU model has a similar architecture with two GRU layers and dropout layers. Additionally, bidirectional LSTM layers are used to capture contextual information from both past and future states in the time series data.

3.3.2 Traditional Machine Learning Models

The traditional machine learning models used include:

- **Linear Regression**: A linear regression model was employed to establish a relationship between the input features and the closing price using the equation:

$$y^{¿}\beta 0+\beta 1\, x 1+\beta 2\, x 2+\cdots+\beta nxn$$

where y^ is the predicted closing price, β0 is the intercept, and β1, β2…, βn are the coefficients of the input features x1, x2…, xn.

- **Decision Tree**: This model used a tree structure where decisions were made based on feature values, splitting data into branches until a prediction was made.
- **Random Forest**: An ensemble method that combined multiple decision trees (each trained on different subsets of the data) to improve prediction accuracy.
- **Gradient Boosting**: A sequential ensemble method that builds trees incrementally, each focusing on the errors of the previous model to improve performance.

- **Support Vector Regression (SVR)**: SVR was used to fit the best hyperplane within a certain margin to predict continuous values.

3.3.3 Ensemble Methods:

Ensemble techniques, such as weighted averaging and stacking, are used to combine the strengths of multiple models and improve overall prediction accuracy.

- **Weighted Averaging**: The final prediction was obtained by averaging the predictions of LSTM, GRU, and Bi-Directional LSTM models, with weights determined by the inverse of the RMSE of each model, where:

    Ensemble Prediction=w1×LSTM Prediction+w2×GRU Prediction+w3n where w1,w2, w3 are the normalised weights based on the inverse RMSE.

- **Stacking**: Stacking involved using the predictions of LSTM, GRU, and Bi-LSTM as inputs to a meta-model (Linear Regression), which then made the final prediction.

3.4 Hyperparameter Tuning

- Grid Search and Random Search were employed for hyperparameter tuning of traditional machine learning models.
- **Keras Tuner**: Used for tuning deep learning models, Keras Tuner helped automate the hyperparameter optimisation process for LSTM, GRU, and Bi-LSTM models by adjusting units, dropout rates, and other parameters.
- **Cross-Validation**: 5-fold cross-validation was used to evaluate the models during the tuning process. This technique involves splitting the dataset into 5 parts, training the model on 4 parts, and testing it on the remaining part. This process is repeated five times with each part serving as the test set once, and the results are averaged:

$$\text{Cross-Validation Score} = \frac{1}{k}\sum_{i=1}^{k} \text{Validation Score}_i$$

where k is the number of folds (in this case, 5).

3.5 Evaluation Metrics

The Metrics used in this study include:

- **Root Mean Squared Error (RMSE)**: Measures the square root of the average squared differences between predicted and actual values, calculated as:

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

where y^i and yi are the predicted and actual values, respectively.

- **Mean Absolute Percentage Error (MAPE)**: Represents prediction accuracy as a percentage:

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|$$

  - **R-squared (R²)**: Indicates the proportion of the variance in the dependent variable that is predictable from the independent variables:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where y¯ is the mean of the actual values.

Source: Evaluation Metric for Regression Models - Analytics Vidhya

- **Justification**: These metrics were chosen because they provide a comprehensive assessment of model performance, especially in a volatile market like cryptocurrency, where understanding both the magnitude and direction of errors is crucial.

3.6 Volatility Analysis

The study analysed the volatility of Bitcoin prices by calculating daily returns and rolling volatility.

- **Daily Returns**: Calculated as the percentage change in closing prices from one day to the next:

$$\text{Daily Return}_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

where Pt is the price at time t and Pt−1 is the price at time t−1.

- **Rolling Volatility**: Measured using a 30-day rolling window to capture short-term fluctuations:

$$\text{Rolling Volatility}_t = \sqrt{\frac{1}{N}\sum_{i=t-N+1}^{t}(\text{Daily Return}_i - \text{Mean Daily Return})^2}$$

where N is the window size (30 days in this study).

- **Significance**: Volatility was incorporated into the predictive models to account for the unpredictable nature of Bitcoin prices.

3.7 Time Series Analysis

3.3.1 Time Series Decomposition

Time series decomposition of the closing prices was performed using the Seasonal-Trend decomposition procedure based on Loess (STL). The decomposition splits the series into four components:

- **Observed (YtY_tYt)**: The original closing price data.
- **Trend (TtT_tTt)**: Represents the long-term movement in Bitcoin's price, highlighting major growth periods, particularly around the peaks of 2017-2018 and 2021.
- **Seasonal (StS_tSt)**: Captures regular patterns or cycles in the data, occurring at specific intervals (e.g., yearly, quarterly). This component showed minor effects that became more pronounced in recent years.
- **Residual (RtR_tRt)**: Represents the noise or random fluctuations after the trend and seasonal components are removed. Significant spikes in residuals were observed during periods of high market volatility, particularly around 2018 and 2021.
- The decomposition is mathematically represented as:

  $Yt = Tt + St + Rt$

3.3.2 ARIMA Model

For forecasting Bitcoin's closing prices, we applied the Autoregressive Integrated Moving Average (ARIMA) model, which is widely used for univariate time series forecasting. The general form of the ARIMA model is:

$ARIMA(p, d, q): \phi p(B)(1-B)dYt = \theta q(B)\epsilon t$

Where:

- p is the order of the autoregressive (AR) term.
- d is the degree of differencing.
- q is the order of the moving average (MA) term.
- B is the backshift operator.
- $\phi p(B)$ and $\theta q(B)$ are polynomials of orders p and q, respectively.
- ϵt is the error term.

3.3.3 SARIMA Model

To incorporate seasonality into the forecasting model, we utilized the Seasonal ARIMA (SARIMA) model, which extends the ARIMA model by adding seasonal components. The general form of the SARIMA model is:

$$SARIMA(p,d,q)(P,D,Q)s:\phi p(B)\Phi P(Bs)(1-B)d(1-Bs)DYt=\theta q(B)\Theta Q(Bs)\epsilon t$$

Where:

- P, D, QP, D, QP,D,Q are the seasonal AR, differencing, and MA terms.
- s is the length of the seasonal cycle.

4. RESULTS AND ANALYSIS

4.1 Exploratory Data Analysis (EDA)

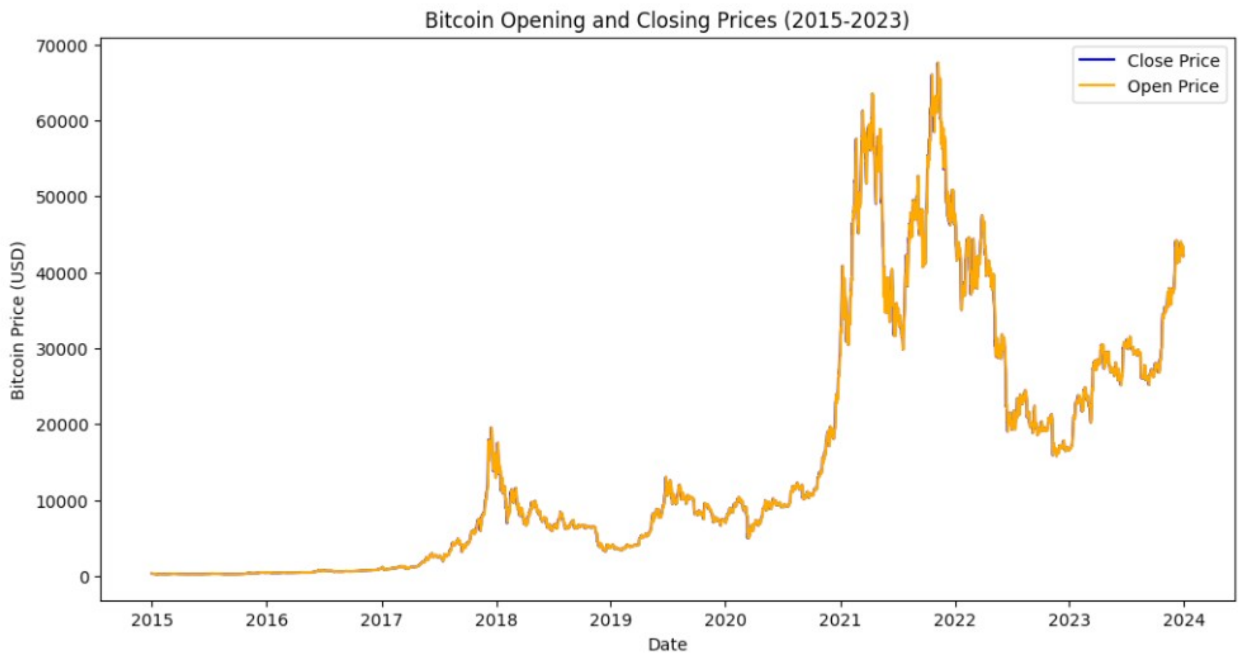


Figure 2:Bitcoin Opening and Closing Prices of Bitcoin (2015-2023)

Figure 2 shows Bitcoin's opening and closing prices from 2015 to 2024, highlighting significant volatility with notable peaks in 2017 and 2021. The data demonstrates a consistent correlation between opening and closing prices, reflecting Bitcoin's characteristic pattern of sharp price increases followed by steep declines, indicative of its speculative nature and market dynamics.

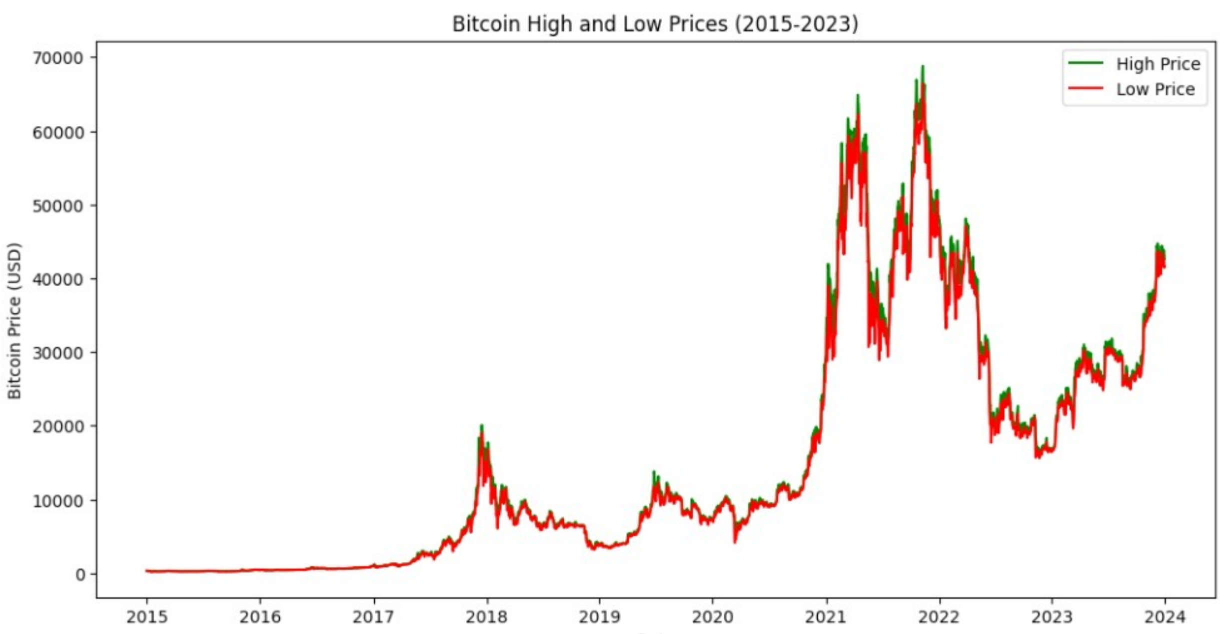


Figure 3: High and Low Prices of Bitcoin (2015-2023)

Figure 3 displays the high and low prices of Bitcoin from 2015 to 2023, showing its significant volatility and notable peaks and troughs, especially in late 2017, early 2021, and mid-2021. The graph also demonstrates the close correlation between high and low prices, indicating rapid intra-day movements characteristic of Bitcoin's market behaviour.

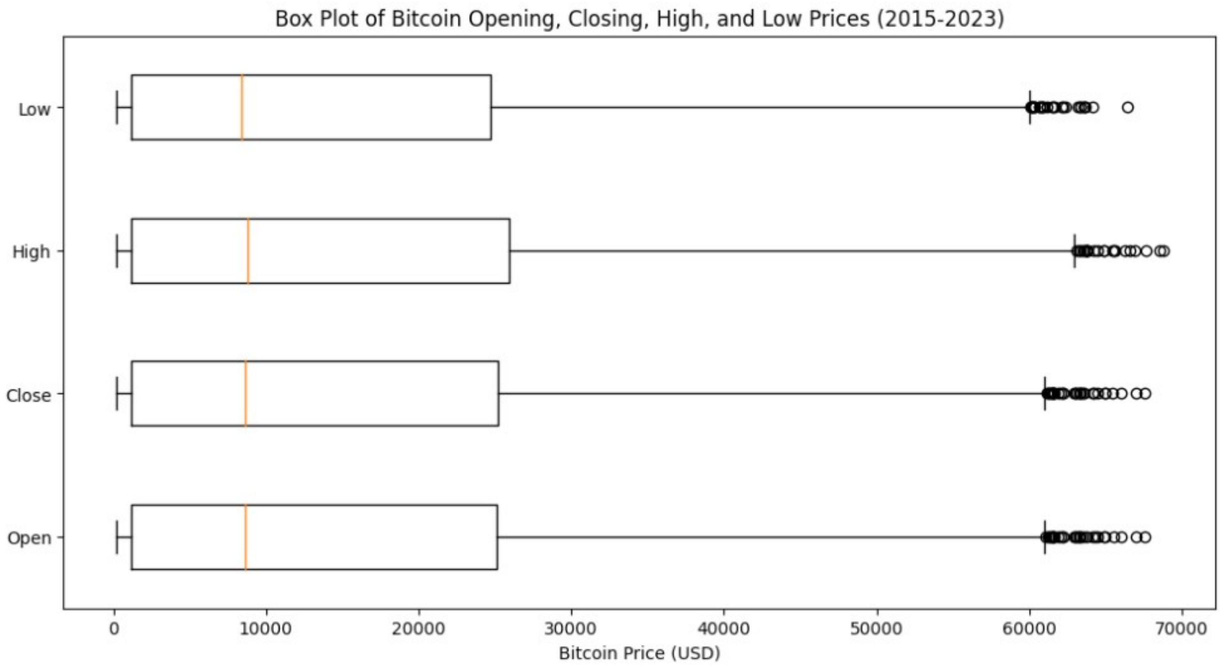


Figure 4: Boxplot of Opening, Closing, High and Low prices of Bitcoin (2015-2023)

In Figure 4, a box plot compares the distribution of Bitcoin's opening, closing, high, and low prices. Most prices fall within a wide range, with some outliers above $60,000. Median prices consistently range from $10,000 to $20,000.

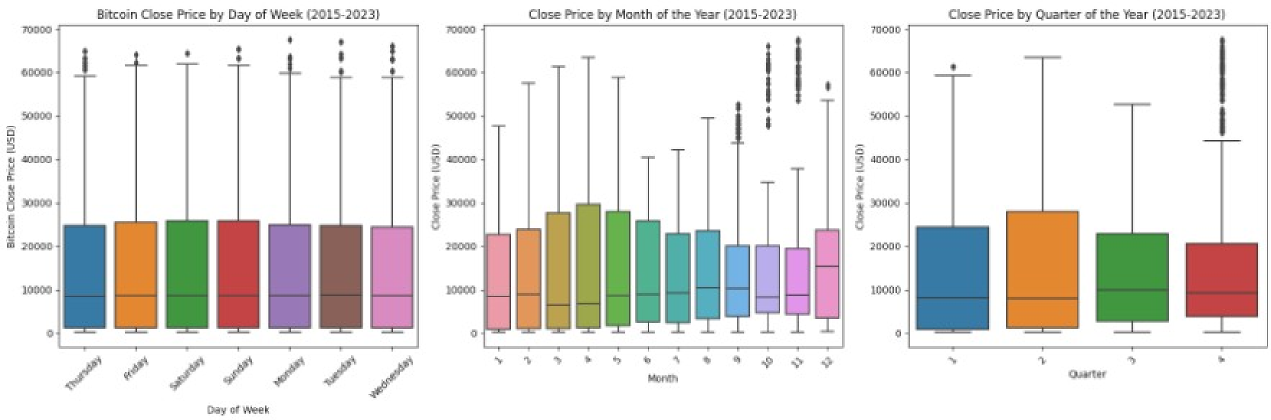


Figure 5: Bitcoin Close Price Analysis by Day, Month, and Quarter (2015-2023)

Figure 5 provide a comprehensive analysis of Bitcoin's closing prices over different time segments from 2015 to 2023. The first plot shows the variation in closing prices across days of the week, indicating a consistent range with slight variations. The second plot examines monthly price fluctuations, highlighting higher price volatility in specific months like September and October. The third plot summarizes the data by quarters, indicating that the second quarter typically experiences more significant price movements compared to other quarters. These visualizations emphasize the influence of temporal factors on Bitcoin's price dynamics.

Figure 5 provides a comprehensive analysis of Bitcoin's closing prices from 2015-2023, showing consistent daily variations, higher monthly volatility in September and October and significant price movements in the second quarter. Appendix 1 shows a detailed view of Bitcoin's market dynamics, with the distribution plot showing most of the closing prices have lower values, while there is a long tail of higher prices. The scatter plots show a positive but variable correlation between trading volumes and closing prices, while the heatmap confirms high correlations among price-related variables and moderate correlation between volume and price variables.

4.2 Statistical analysis of the data.

Table 1 shows a summary of the statistics for Bitcoin's historical prices and trading volume from 2015 to 2023. The dataset comprises 3,286 observations. The average closing price over this period was $15,033.34, indicating a high level of volatility, with a standard deviation of $16,237.73. The lowest recorded closing price was $178.10, while the highest was $67,566.83. The trading volume showed significant variation, with an average of around $17.08 billion and a peak of $350.97 billion. These statistics illustrate the volatile and high-stakes nature of the Bitcoin market during this period.

4.3 Evaluation of the Performances of Machine Learning Models Before and After Hyperparameter Tuning

Tables 2, 3, and 4, shows significant enhancements in the performance of various machine learning models post hyperparameter tuning. Decision Tree, Random Forest, and Gradient Boosting demonstrated moderate improvements in prediction accuracy. Specifically, the SVR model displayed a substantial reduction in RMSE from 0.0669 to 0.0143 and an increase in R^2 from 0.6291 to 0.9830. LSTM, GRU, and Bi-LSTM also saw improvements post tuning, with LSTM achieving the best overall performance with an RMSE of 0.0136 and R^2 of 0.9847. Among ensemble methods, the Stacked Ensemble model outperformed others, achieving an RMSE of 0.0124 and R^2 of 0.9874 post tuning, making it the most effective model in predicting Bitcoin prices in this study. These results emphasize the significance of hyperparameter tuning in enhancing model accuracy.

Table 1: Summary Statistics of Bitcoin Prices (2015 - 2023)

Statistic	Open Price ($)	High Price ($)	Low Price ($)	Close Price ($)	Volume (Coins)
Count	3,286	3,286	3,286	3,286	3,286
Mean	15,021.97	15,373.27	14,643.64	15,033.34	17,082,100
Std	16,235.87	16,625.79	15,798.24	16,237.73	19,156,900
Min	176.90	211.73	171.51	178.10	7,860.65
25%	1,184.26	1206.20	1,172.05	1,187.83	333,800,000
50%	8,639.33	8,818.12	8,382.11	8,659.02	12,771,980,000
75%	25,105.04	25,912.47	24,728.55	25,153.16	27,420,280,000
Max	67,549.73	68,789.63	66,382.06	67,566.83	350,967,900,000

Table 2: Summary of Traditional Machine Learning Models Performance (Before and After Tuning)

Model	**Before Hyper tunning**				**After Hyper tunning**		
	RMSE	**MAPE**	**R^2**	**Cross-Validated RMSE**	**RMSE**	**MAPE**	**R^2**
Decision Tree	0.0536	0.1287	0.7619	0.1965	0.0769	0.1966	0.5101
Random Forest	0.0600	0.1517	0.7020	0.2056	0.0783	0.2023	0.4928
Gradient Boosting	0.0570	0.1304	0.7307	0.2023	0.0694	0.1632	0.6012
SVR	**0.0669**	**0.1719**	**0.6291**	**0.2419**	**0.0143**	**0.0274**	**0.9830**
Linear Regression	0.0157	0.0303	0.9795	0.0173	-	-	-

Table 3: Performance of Deep Learning Models (Before and After Hyperparameter Tuning)

	Before Hyper tunning			**After Hyper tunning**		
Model	**RMSE**	**MAPE**	**R^2**	**RMSE**	**MAPE**	**R^2**
LSTM	0.0304	0.0535	0.9232	0.0136	0.0263	0.9847
GRU	0.0200	0.0352	0.9669	0.0141	0.0300	0.9835
Bi-LSTM	0.0247	0.0442	0.9494	0.0147	0.0310	0.9820

Table 4:Performance of Ensemble Models Before and After Hyperparameter Tuning

	Before Hyper tunning			**After Hyper tunning**		
Model	**RMSE**	**MAPE**	**R^2**	**RMSE**	**MAPE**	**R^2**
Bagged Linear Regression	0.0147	0.0277	0.9821	-	-	-
Bagged Decision Tree	0.0532	0.1318	0.7659	-	-	-
Bagged SVR	0.0754	0.1949	0.1949	-	-	-
Boosted Decision Tree	0.0666	0.1735	0.6325	-	-	-
Weighted Ensemble	0.0236	0.0419	0.9539	0.0136	0.0283	0.9846
Stacked Ensemble	**0.0169**	**0.0308**	**0.9764**	**0.0124**	**0.0229**	**0.9874**

4.4 Time series Analysis

The time series analysis of Bitcoin's closing prices involved decomposing the data into its components: observed data, trend, seasonality, and residuals. The trend component highlighted significant long-term growth, particularly during the peaks in 2017-2018 and 2021. The seasonal effects were minor but gradually increased over time, while the residuals revealed periods of heightened volatility, especially around the market events of 2018 and 2021.

In evaluating predictive models, both ARIMA and SARIMA were applied to forecast Bitcoin prices. The ARIMA model struggled to capture the significant fluctuations inherent in Bitcoin's volatile market, leading to constant value predictions that deviated substantially from actual prices. Similarly, the SARIMA model, though slightly better at identifying long-term trends, also failed to accurately predict short-term price movements due to the high volatility and rapid changes in Bitcoin prices.

The performance metrics for these models, summarised in Table 5, show significant prediction errors and negative R^2 values, indicating their limitations in effectively forecasting Bitcoin prices in such a dynamic environment.

Table 5: Performance Metrics of ARIMA and SARIMA Models

Model	RMSE	MAPE	R^2
ARIMA	13,952.51	0.5581	-2.3834
SARIMA	18,462.84	0.7436	-4.9244

4.5 Bitcoin Price and Volatility Analysis

The analysis of Bitcoin's price and volatility reveals a strong correlation between significant price movements and increased volatility. Periods of rapid price surges, such as in 2017 and 2021, are marked by heightened volatility, which often remains elevated even after the price stabilises or declines, indicating ongoing market uncertainty.

4.5.1 Daily Returns on Bitcoin (2015-2023)

Figure 6 shows the frequent and sharp price changes in Bitcoin, with a visible spike in returns during these periods. The data shows the consistent fluctuations in daily returns over time, underscoring the erratic nature of Bitcoin's market behaviour.

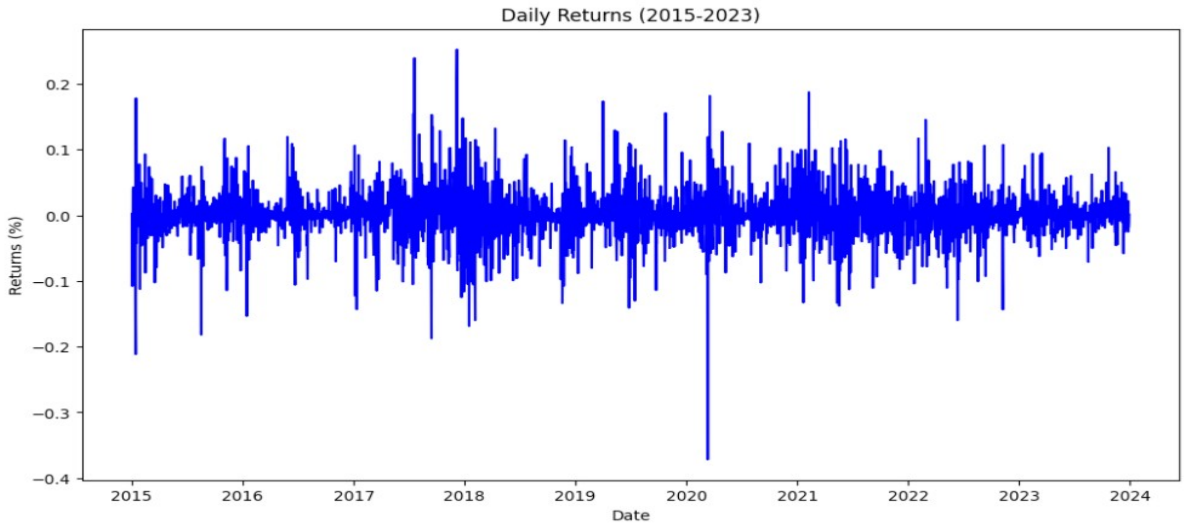


Figure 6:Daily Returns on Bitcoin (2015-2023)

4.5.2 Bitcoin (BTC-USD) Volatility and Daily Return Analysis

The graph shows the volatility of BTC-USD (Bitcoin to USD) from 2015 to 2023. The 7-day volatility (in blue) is more erratic and spikes frequently, while the 30-day volatility (in black) is smoother but follows a similar pattern. Volatility was particularly high during late 2017, early 2018, and mid-2020, with notable spikes. In recent years, volatility has decreased but still experiences occasional surges.

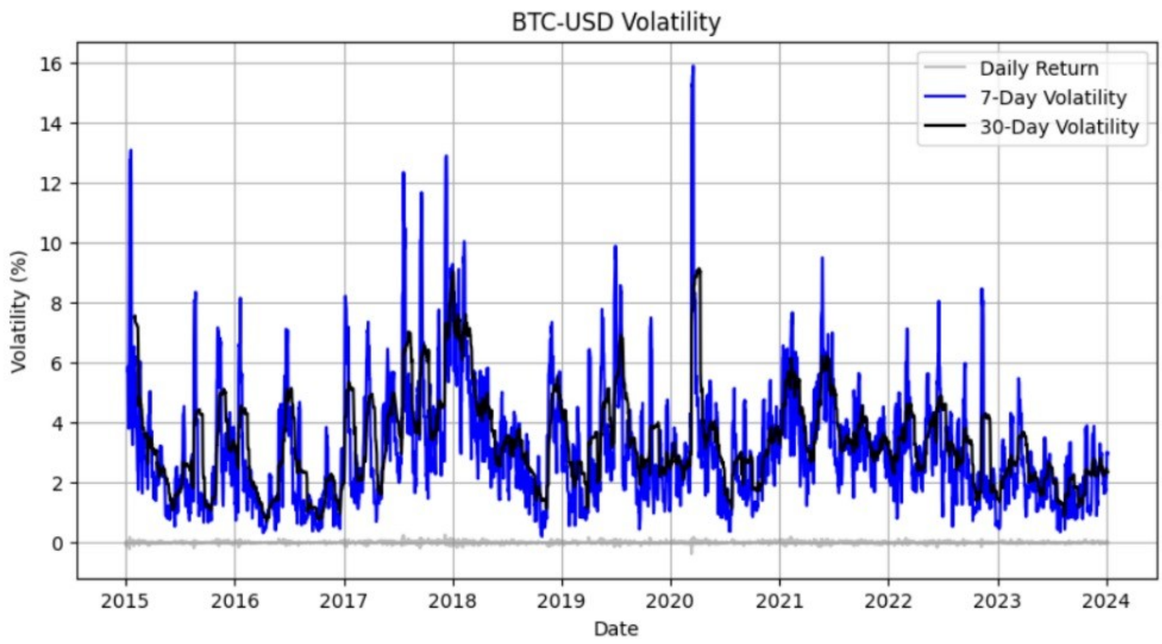


Figure 7 : Bitcoin (BTC-USD) Volatility and Daily Return Analysis

4.5.3 Bitcoin Price Volatility (2015-2023)

The graph shows that the major price movements are closely followed by significant increases in volatility. The periods of rapid price surges and subsequent stabilization highlight the ongoing market uncertainty that needs to be considered in predictive models.

These findings underscore the importance of accounting for volatility when predicting Bitcoin prices, as it significantly influences the accuracy and reliability of forecasting models.

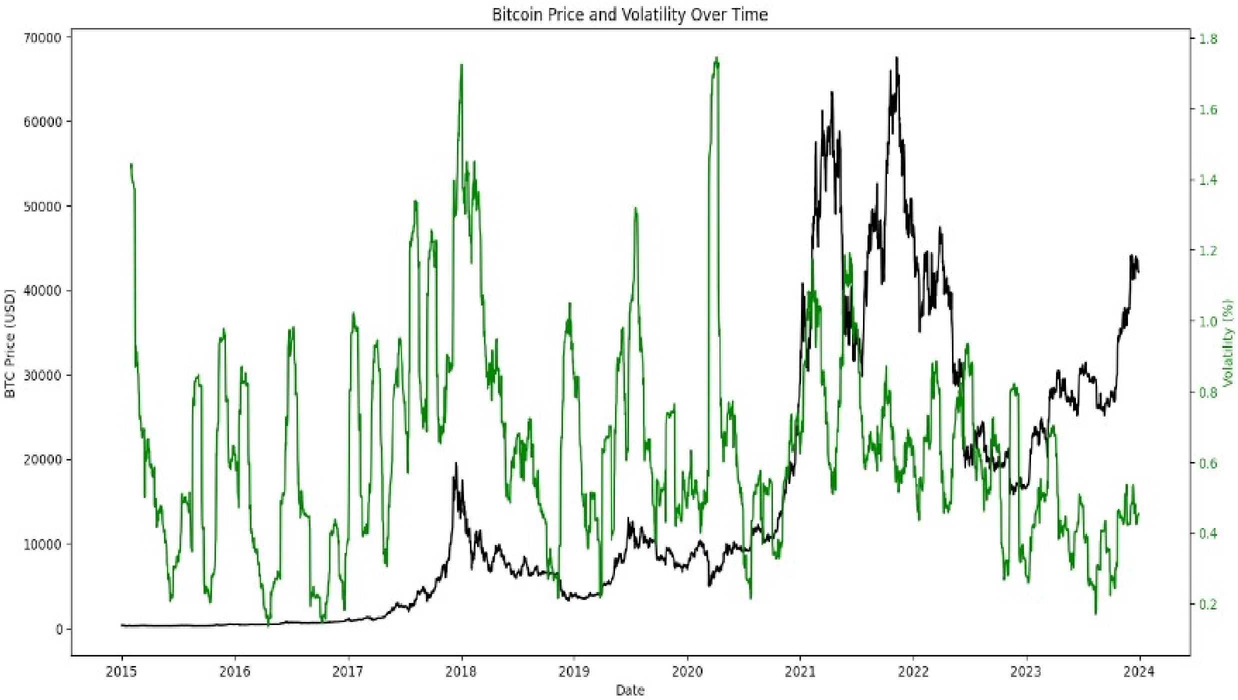


Figure 8: Bitcoin Price and Volatility (2015-2023)

4.6 Bitcoin Price Prediction for the week ending 06-01-2024

The predicted prices as shown in Figure 9, represents by the red dashed line, projecting a slight increase in Bitcoin's value over the next seven days from December 31, 2023, to January 6, 2024. Table 6 provides a comparison between the actual prices observed at the end of December 2023 and the predicted prices:

This summary indicates that the predicted prices are generally slightly higher than the actual prices, suggesting a moderate upward trend in Bitcoin prices as forecasted by the Tuned Ensemble Stacking Model.

The plot above titled "Historical and Predicted Prices for the Next Seven Days using the Tuned Ensemble Stacking Model" shows the historical prices of Bitcoin alongside the predicted prices for the first week of January 2024. The historical prices, depicted in black, trace the trend from 2015 through the end of 2023, showing significant fluctuations, particularly during the 2017-2018 and 2021-2022 periods.

Table 6: Actual and Predicted Bitcoin Prices (31-12-2023 - 06-01-2023)

DATE	ACTUAL PRICE	PREDICTED PRICE
2023-12-31	$42,265.1875	$42,832.0100
2024-01-01	$44,167.3320	$43,484.2104
2024-01-02	$44,957.9688	$43,590.3650
2024-01-03	$42,848.1758	$44,336.1800
2024-01-04	$44,179.9219	$45,006.8608
2024-01-05	$44,162.6914	$45,737.5840
2024-01-06	$43,989.1953	$46,525.8762

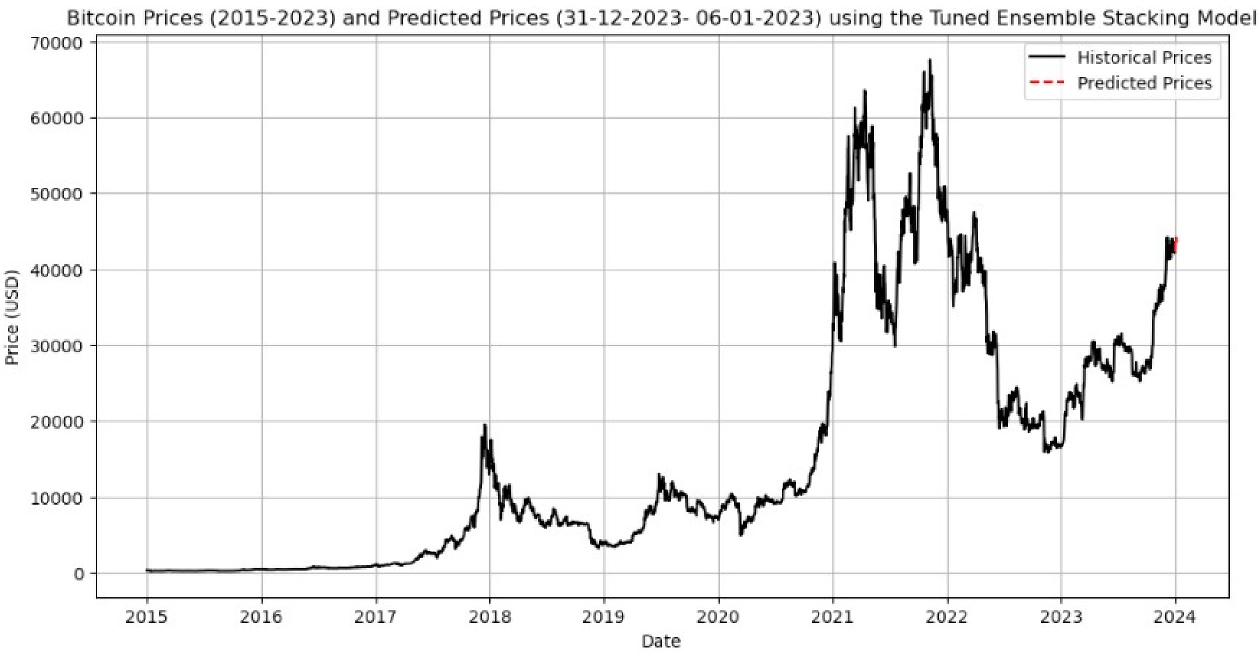


Figure 9: Plot of Predicted Bitcoin Prices using The Tuned Stacked Ensemble Model

5. DISCUSSION AND CONCLUSION

5.1 Key Findings

This study examined the use of various deep learning and traditional machine learning models to predict Bitcoin prices, focusing on models like LSTM, GRU, Bi-Directional LSTM, Linear Regression, Decision Tree, Random Forest, Gradient Boosting, and SVR. The analysis revealed that deep learning models, particularly LSTM and the Stacked Ensemble, provided the most accurate predictions, especially after hyperparameter tuning.

These models effectively captured Bitcoin's complex and nonlinear price patterns, outperforming traditional machine learning approaches and highlighted the significant impact of Bitcoin's volatility on prediction accuracy, with traditional models like ARIMA and SARIMA struggling to handle rapid price changes, resulting in high prediction errors and negative R^2 values.

5.2 Comparison with Existing Literature

Valencia et al. (2019) and Chen et al. (2020) showed the superiority of deep learning models like LSTM in handling complex, high-frequency financial data, which is consistent with results from this study

This study also underscored the challenges posed by Bitcoin's inherent volatility which aligns with Guo et al. (2021) study that highlighted the limitations of traditional models such as ARIMA and SARIMA in capturing the rapid price fluctuations typical of cryptocurrency markets.

5.3 Implications for Financial Markets

The insights from this study have practical implications for trading and investment strategies. The superior performance of deep learning models suggests their potential application in the highly volatile risk averse cryptocurrency markets. Investors and traders could use these models to improve decision-making, optimize trading strategies, and manage risk more effectively

The study also highlights the critical role of hyperparameter tuning in improving model performance Singh et al. (2022) and Girsang (2023.

5.4 Challenges and Limitations

The data used was limited to historical price and volume information, which may have constrained the models' ability to capture all relevant factors influencing Bitcoin prices. Additionally, the study's models were primarily evaluated on their ability to predict short-term price movements, which may not fully reflect their performance over longer periods or under different market conditions.

5.5 Recommendations for Future Research

Given the dynamic nature of cryptocurrency markets, future research should explore more sophisticated models or hybrid approaches that can better accommodate the complexities of these markets. Amirshahi and Lahmiri (2023) and Tapia and Kristjanpoller (2022). Expanding the study to include other cryptocurrencies or financial assets could provide further insights into the generalisability of the findings.

5.6 Conclusion

This study demonstrated that deep learning models, particularly LSTM and Stacked Ensemble, are highly effective in predicting Bitcoin prices when appropriately tuned. The analysis also emphasised the challenges posed by Bitcoin's volatility, suggesting that future research should explore more sophisticated models or hybrid approaches that can better accommodate the dynamic nature of cryptocurrency markets. Hyperparameter tuning emerged as a crucial step in enhancing model performance, making it a key consideration for future predictive modelling efforts.

Reference list / Bibliography

AlMadany, N.N., Hujran, O., Al Naymat, G., & Maghyereh, A. (2024). Forecasting cryptocurrency returns using classical statistical and deep learning techniques. *International Journal of Information Management Data Insights*, 4(2), p.100251.

Amirshahi, B. and Lahmiri, S., 2023. Hybrid deep learning and GARCH-family models for forecasting volatility of cryptocurrencies. *Machine Learning with Applications*, 12, p.100465. https://doi.org/10.1016/j.mlwa.2023.100465.

Amirzadeh, R., Nazari, A., & Thiruvady, D. (2022). Applying artificial intelligence in cryptocurrency markets: A survey. *Algorithms*, 15(11), p.428. https://doi.org/10.3390/a15110428

Amirzadeh, R., Nazari, A., Thiruvady, D., & Ee, M. (2023). Modelling determinants of cryptocurrency prices: A Bayesian network approach. *arXiv*. Available at: https://doi.org/10.48550/arxiv.2303.16148 [Accessed 20 Aug. 2024].

Akyildirim, E., Goncu, A., Sensoy, A., & Gupta, R. (2021). Predictability of cryptocurrency returns using support vector machines. *Journal of Economic Behavior & Organization*, 182, pp. 342-359. https://doi.org/10.1016/j.jebo.2021.01.009

Chen, J., Li, C., & Sun, W. (2020). Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics*, 365, p.112395. https://doi.org/10.1016/j.cam.2020.112395

Girsang, A. (2023). Hybrid LSTM and GRU for cryptocurrency price forecasting based on social network sentiment analysis using FinBERT. *IEEE Access*, 11, pp. 120530-120540. https://doi.org/10.1109/access.2023.3324535

Guo, H., Zhang, D., Liu, S., Wang, L., & Ding, Y. (2021). Bitcoin price forecasting: A perspective of underlying blockchain transactions. *Decision Support Systems*, 151, Article 113650. https://doi.org/10.1016/j.dss.2021.113650

Heaton, J., Polson, N., & Witte, J. (2017). Deep learning for finance: Deep portfolios. *Applied Stochastic Models in Business and Industry*, 33(1), pp. 3-12.

Jones, J., & Demirel, T. (2022). Bitcoin price prediction using LSTM: A machine learning approach. *IEEE Transactions on Computational Social Systems*, 9(4), pp. 1032-1041. https://doi.org/10.1109/TCSS.2022.3156237

Khan, F.U., Khan, F., & Shaikh, P.A. (2023). Forecasting returns volatility of cryptocurrency by applying various deep learning algorithms. *Future Business Journal*, 9, p.25. https://doi.org/10.1186/s43093-023-00200-9

MohammadJafari, A. (2024). Comparative Study of Bitcoin Price Prediction. School of Computing and Informatics, University of Louisiana at Lafayette, USA. Available at: https://arxiv.org/abs/2405.08089v1 [Accessed 10 August 2024].

Nakamoto, S. (2008) *Bitcoin: A peer-to-peer electronic cash system*. Available at: https://bitcoin.org/bitcoin.pdf (Accessed: [Accessed 10 August 2024]).

Patel, J., Kalariya, V., Parmar, P., Tanwar, S., Kumar, N., & Alazab, M. (2020). Stochastic neural networks for cryptocurrency price prediction. *IEEE Access*, 8, pp. 82804-82818. https://doi.org/10.1109/access.2020.2990659

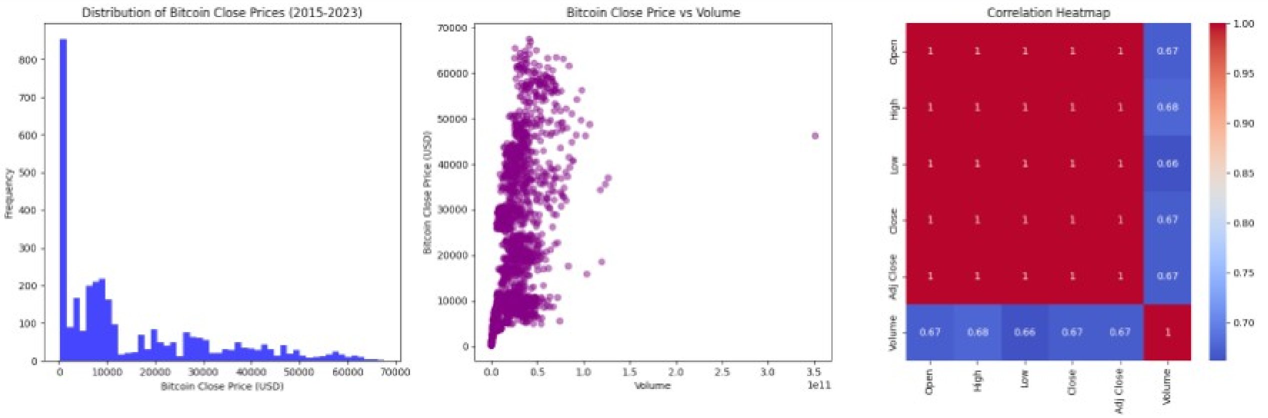
Poongodi, M., Sharma, A., & Mohanty, S. (2020). Bitcoin price prediction using ARIMA model. *Journal of Computer Networks and Communications*, 2020, pp. 1-9.

Tapia, J., & Kristjanpoller, F. (2022). Bitcoin volatility prediction using LSTM and multiplicative error models. *International Journal of Forecasting*, 38(4), pp. 1321-1332.

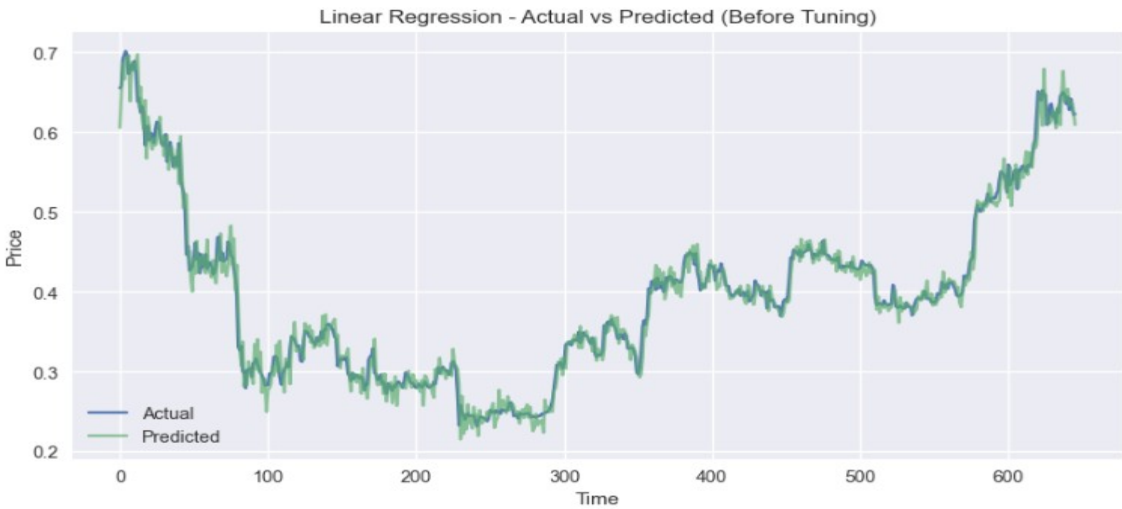
Valencia, F., Gómez-Espinosa, A., & Valdés-Aguirre, B. (2019). Price movement prediction of cryptocurrencies using sentiment analysis and machine learning. *Entropy*, 21(6), p.589. https://doi.org/10.3390/e21060589

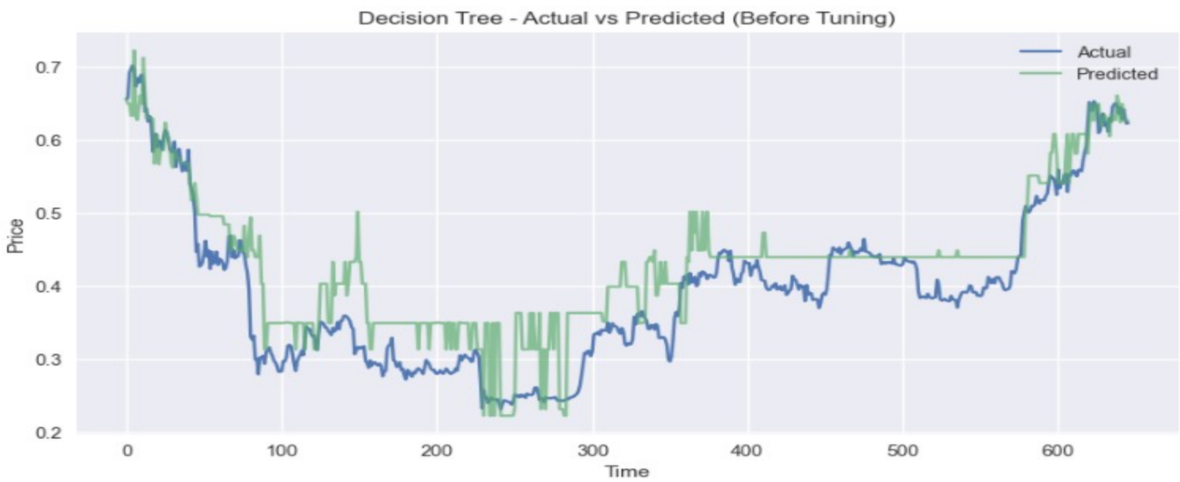
Zuo, A. (2024). Comparison and analysis of the accuracy of various machine learning algorithms in Bitcoin price prediction. *Advances in Economics Management and Political Sciences*, 70(1), pp. 302-308. https://doi.org/10.54254/2754-1169/70/20231726

Appendix 1 Plots

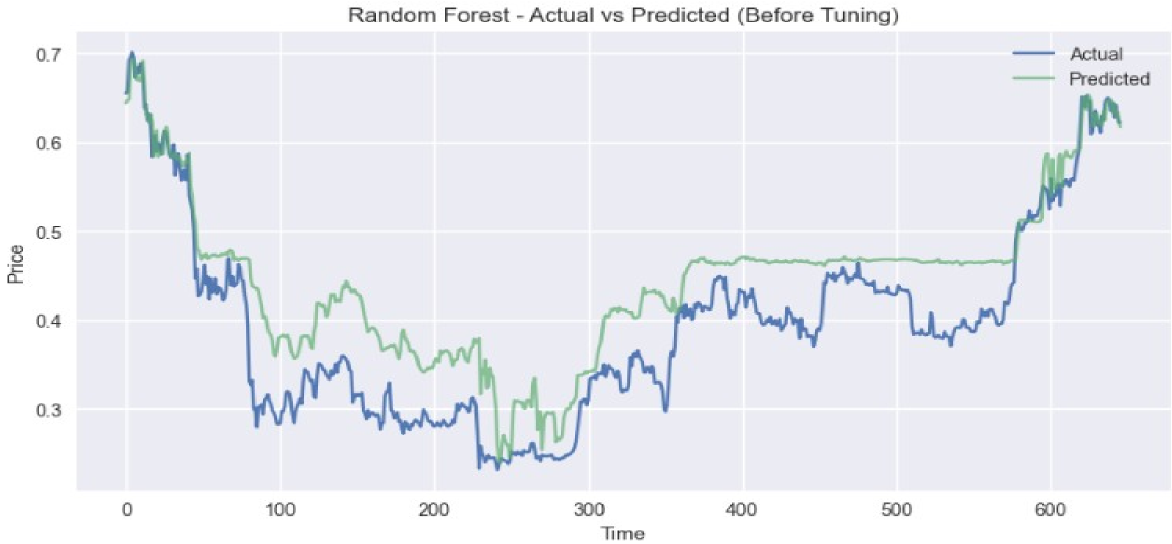


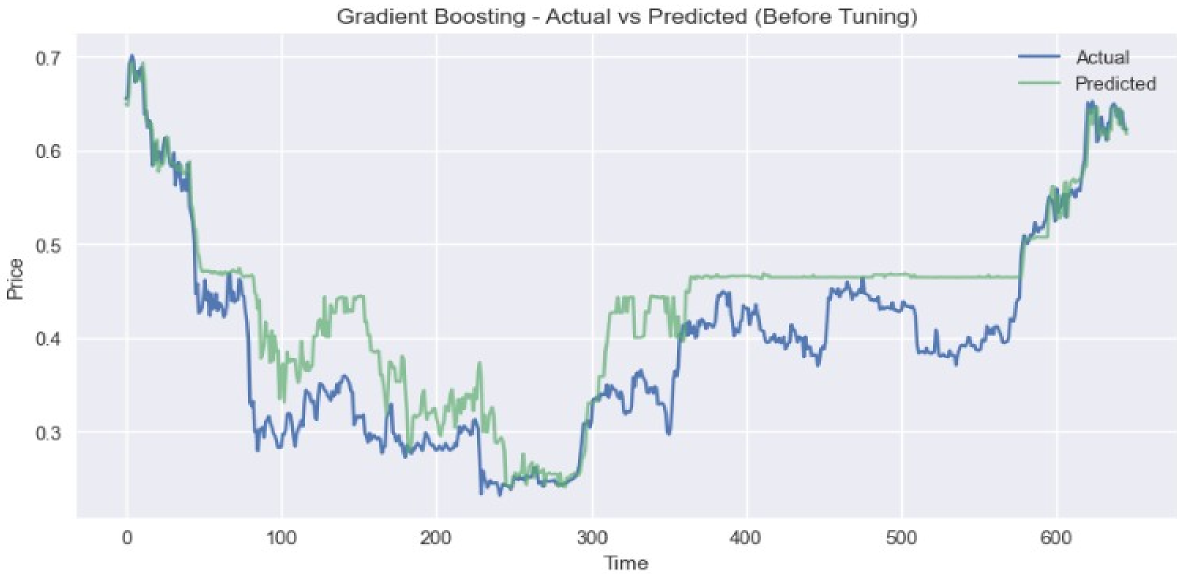
Analysis of Bitcoin Close Prices, Volume, and Correlations (2015-2023)

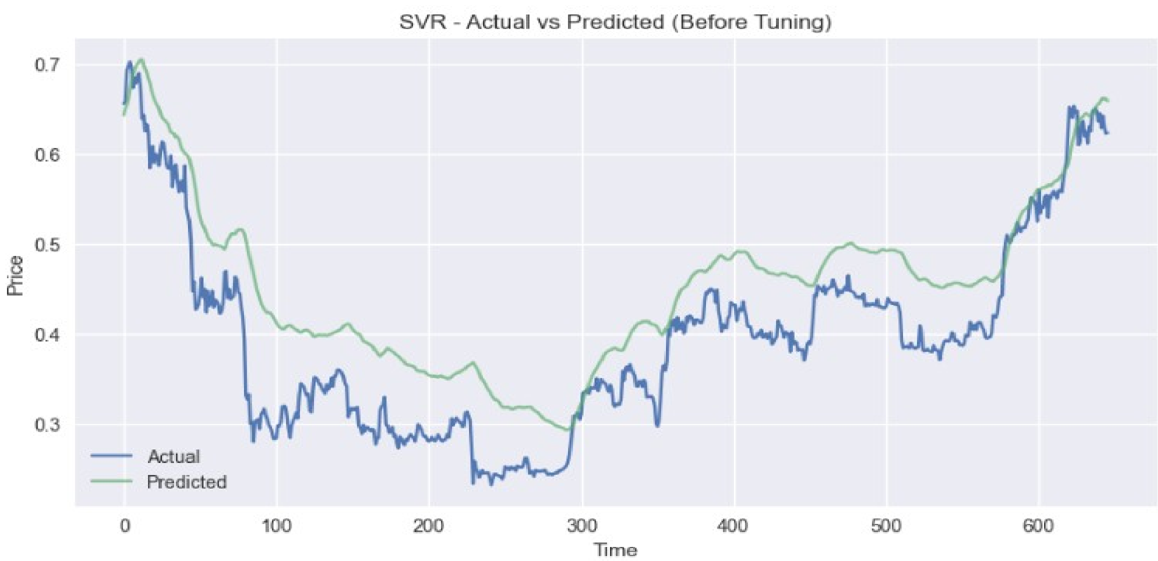


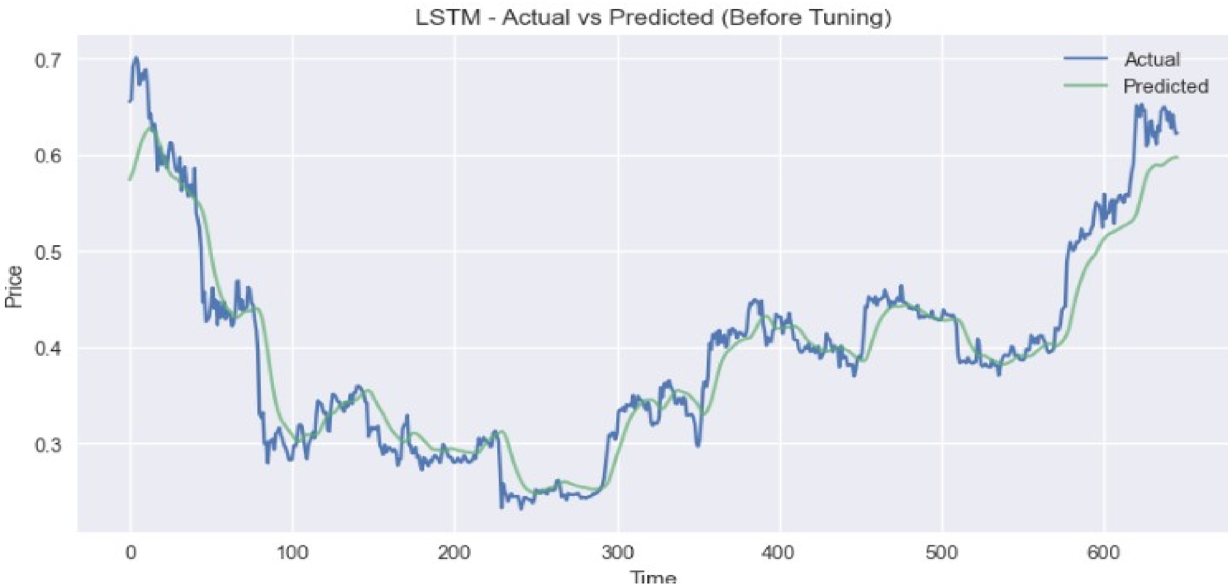


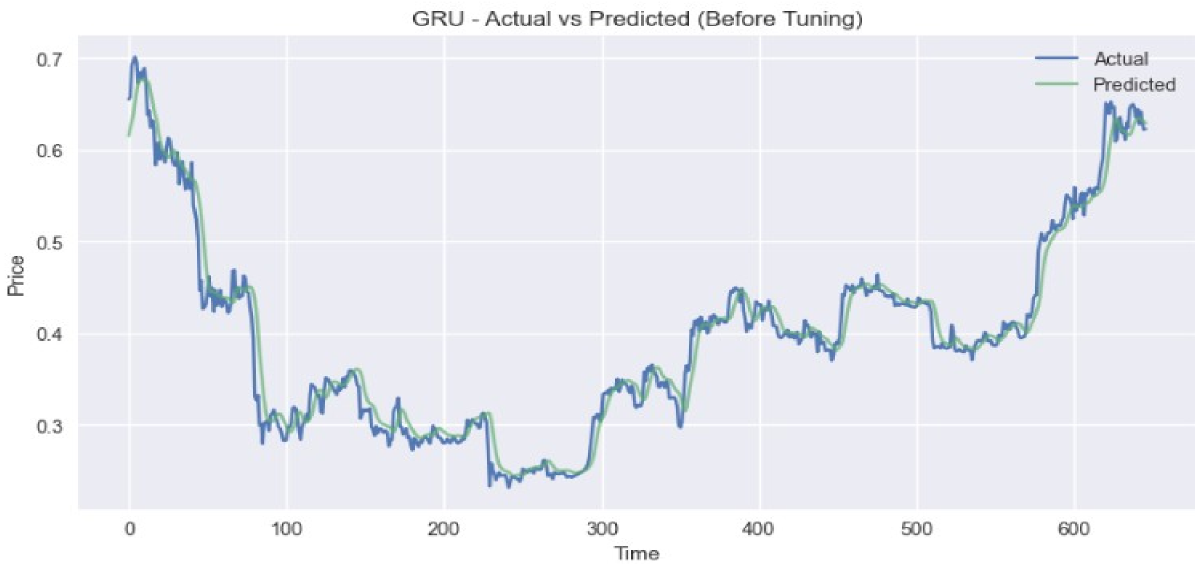
Random Forest - Actual vs Predicted (Before Tuning)


Random Forest - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

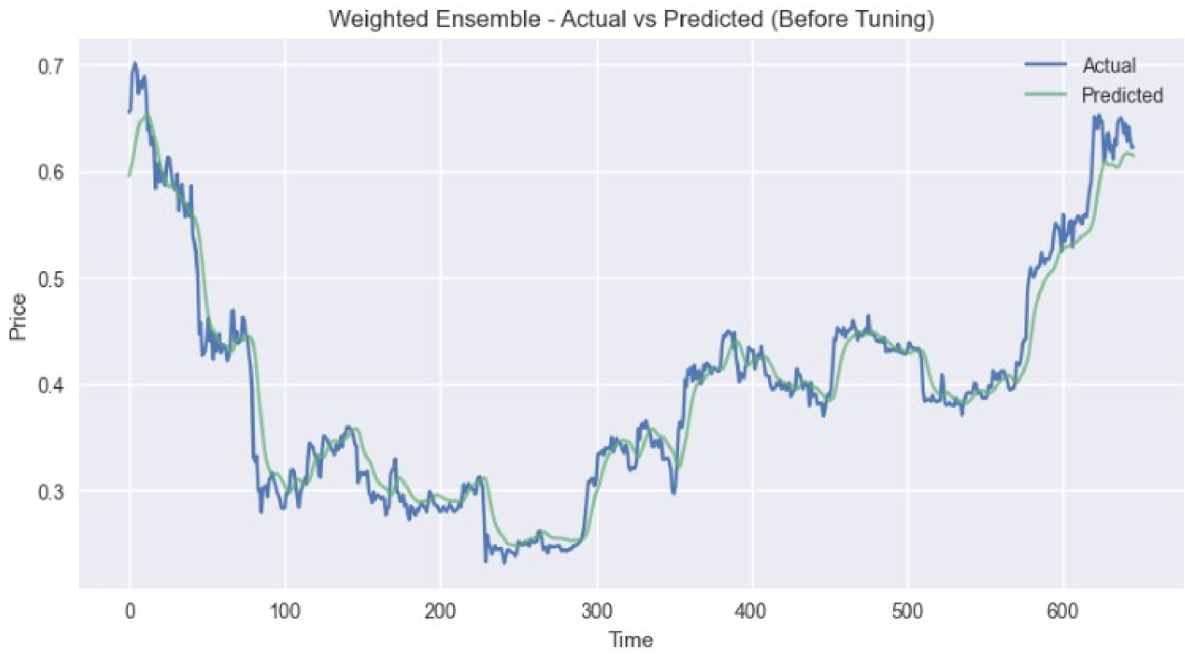

Gradient Boosting - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

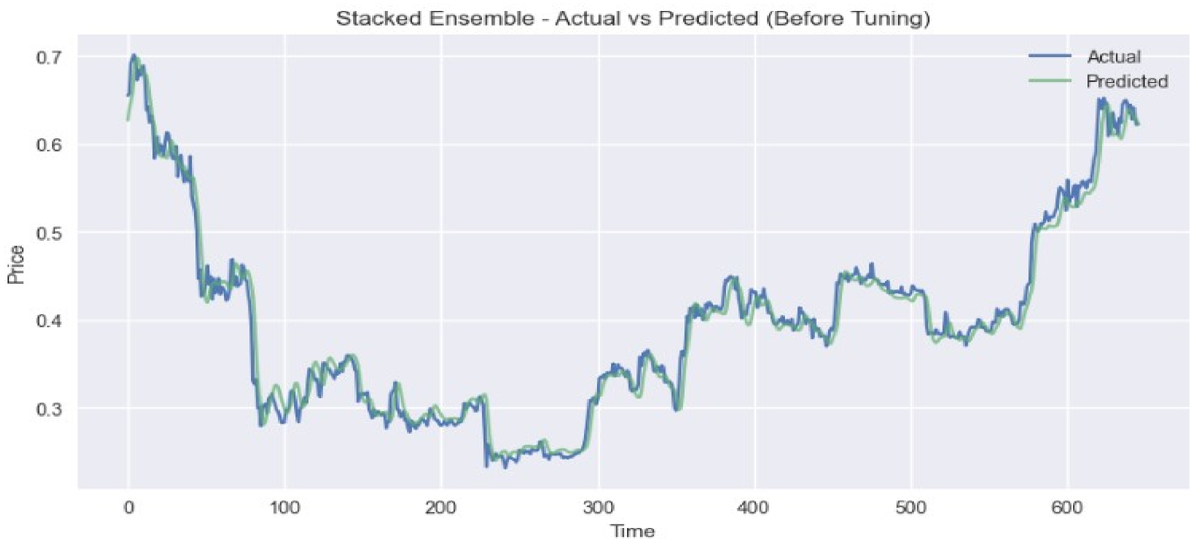

SVR - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

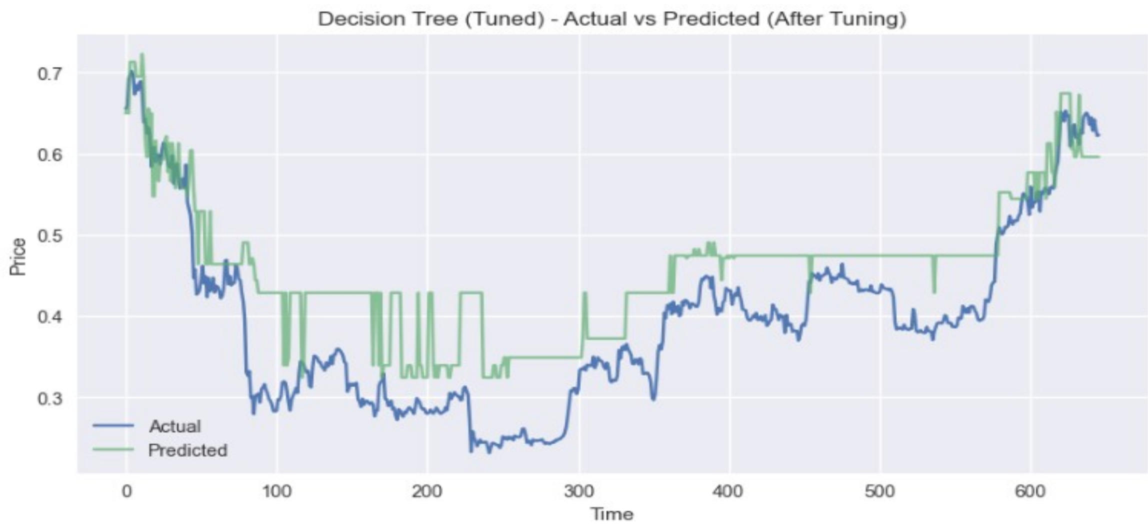

LSTM - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600


GRU - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

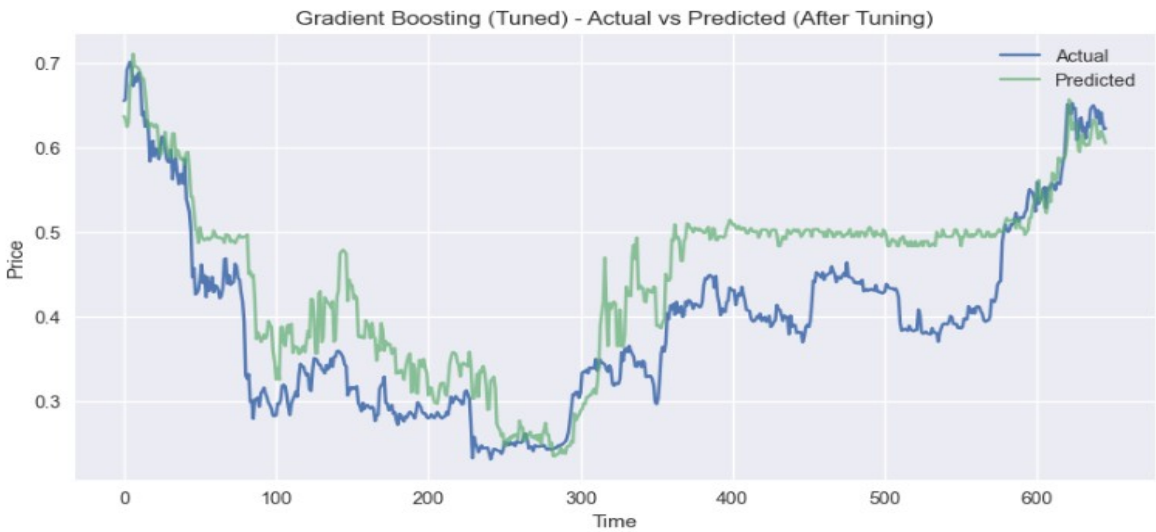

Bi-LSTM - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

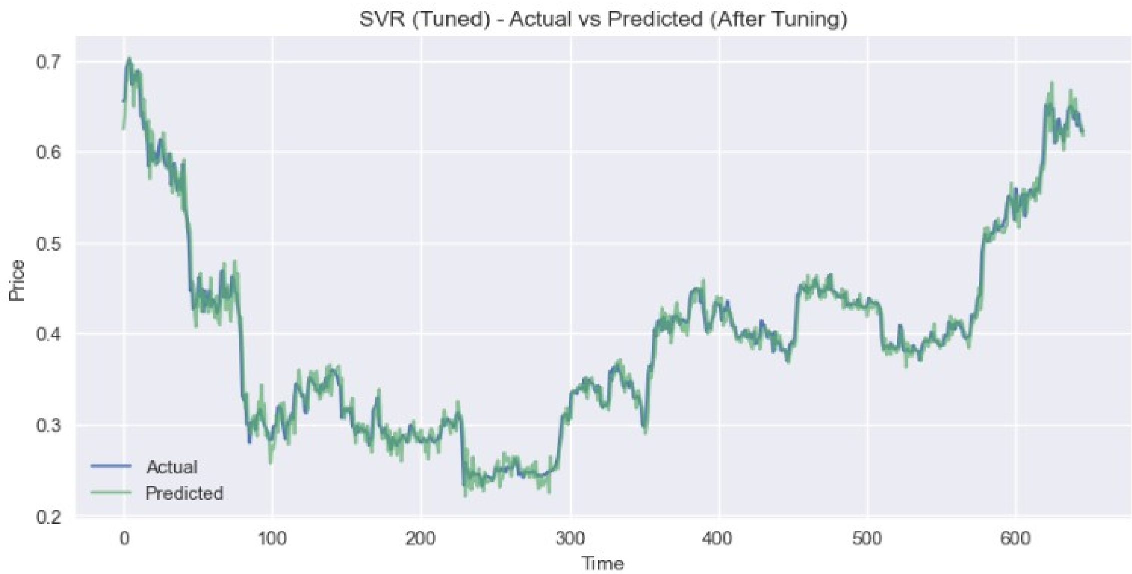

Weighted Ensemble - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600


Stacked Ensemble - Actual vs Predicted (Before Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

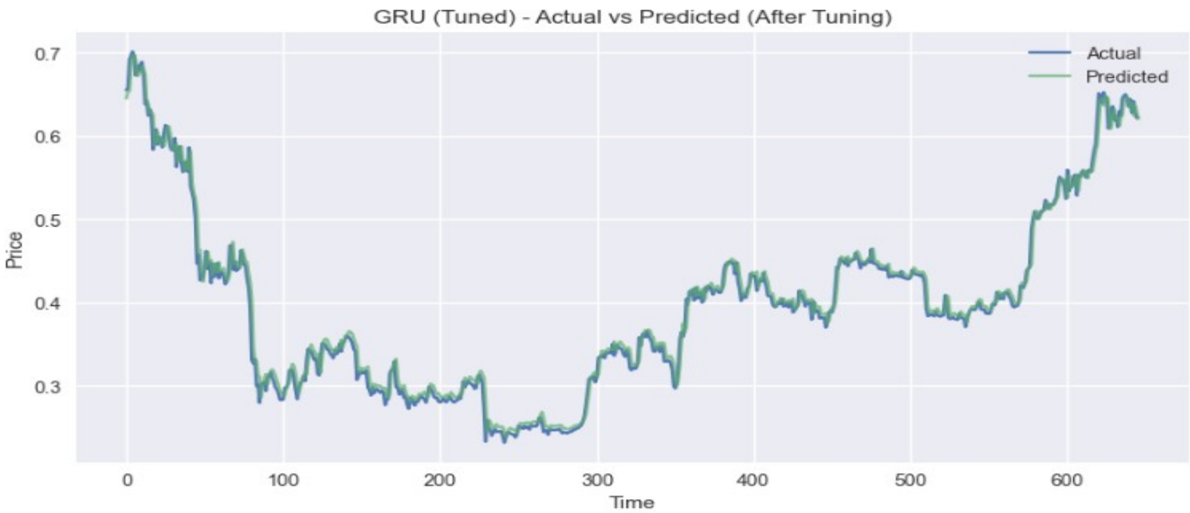

Decision Tree (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

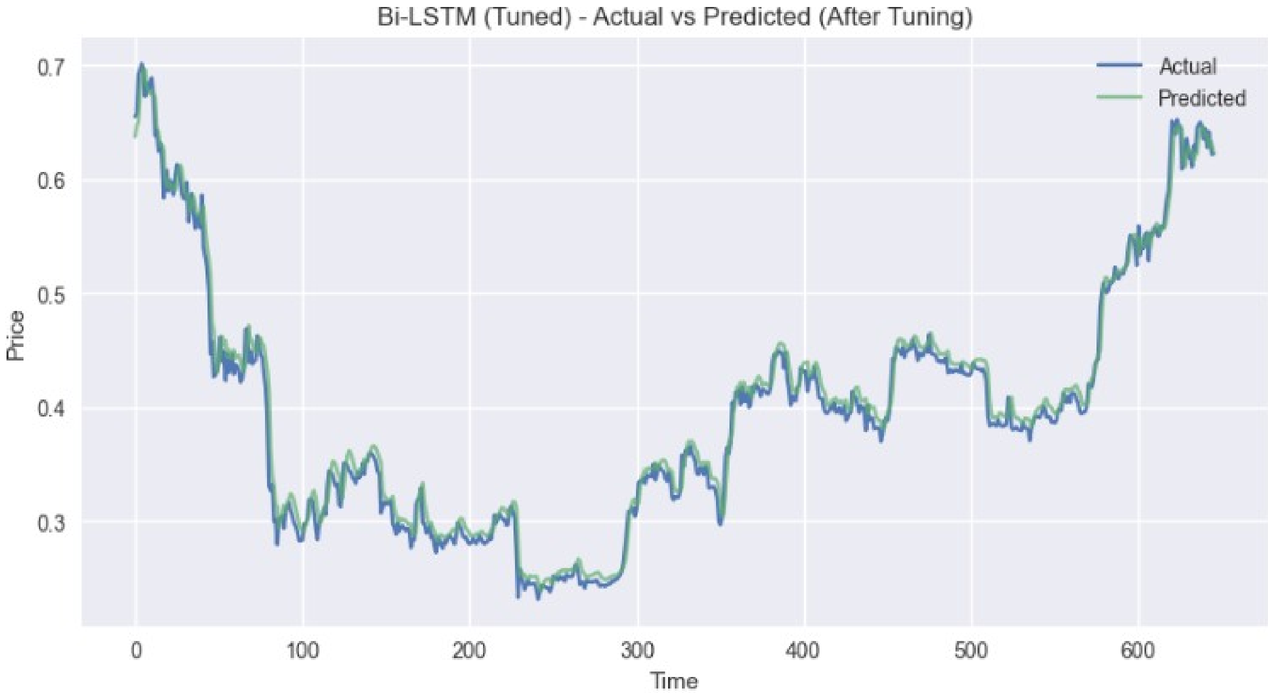

Random Forest (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
Time


Gradient Boosting (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
Time

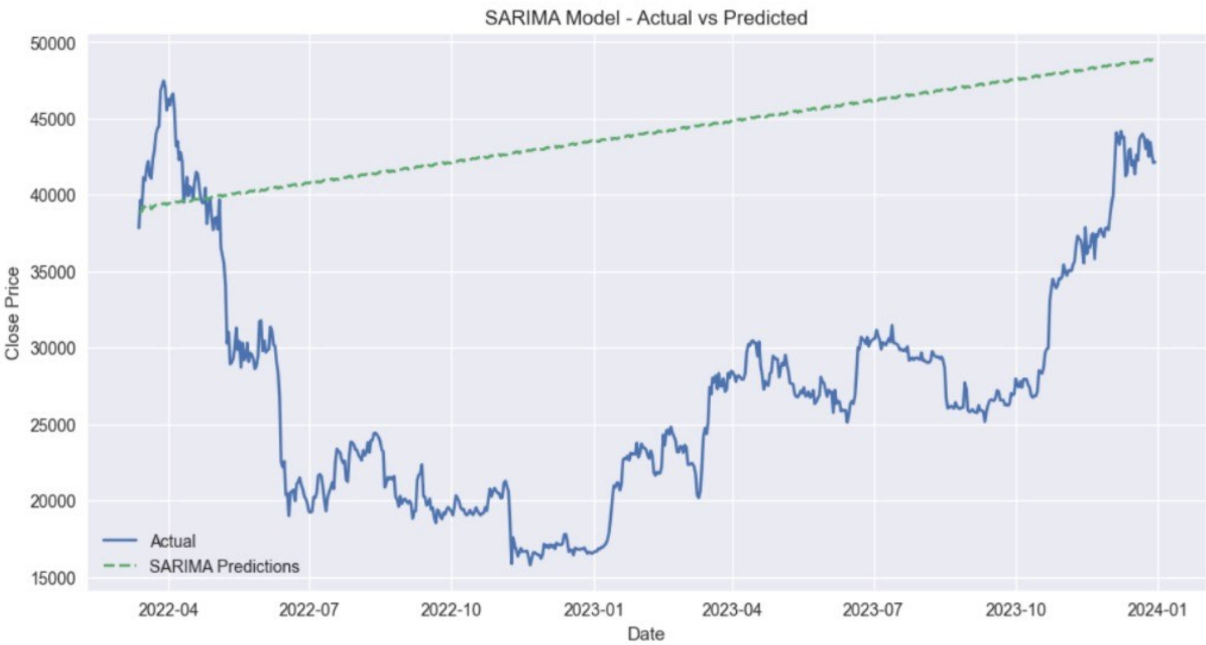

SVR (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
Time

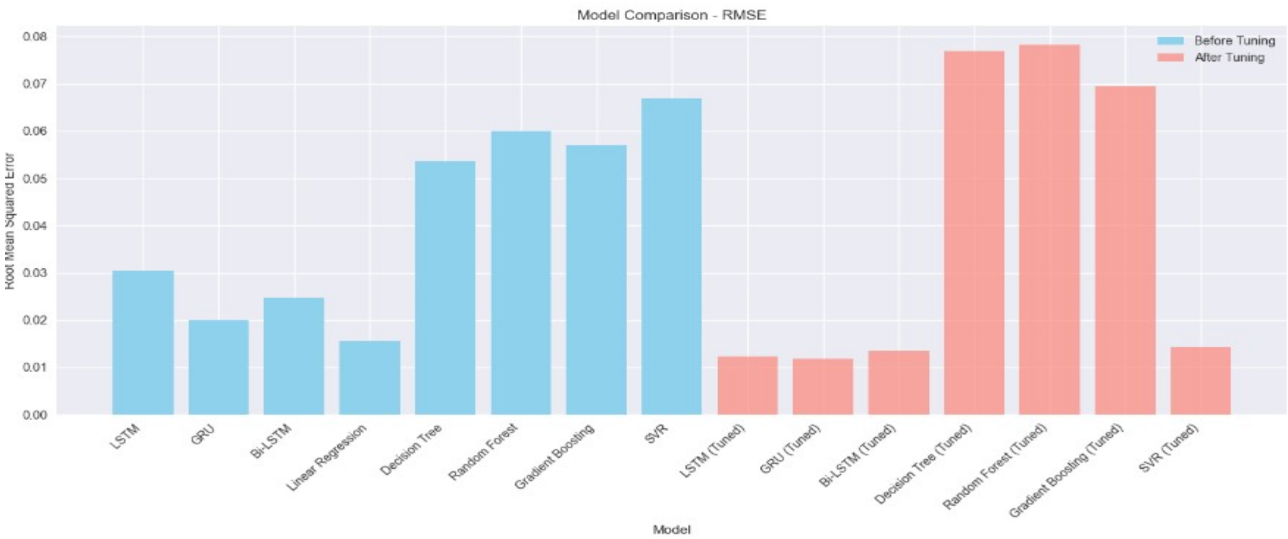

LSTM (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

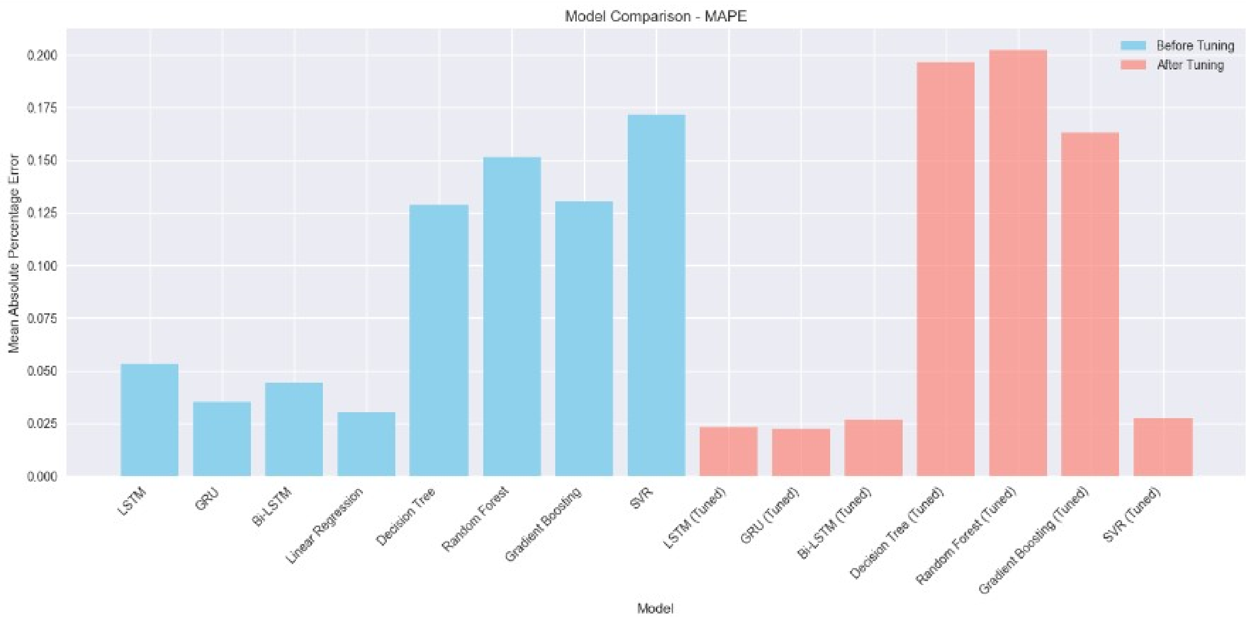

GRU (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
Time
0.7
0.6
0.5
0.4
0.3
0
100
200
300
400
500
600

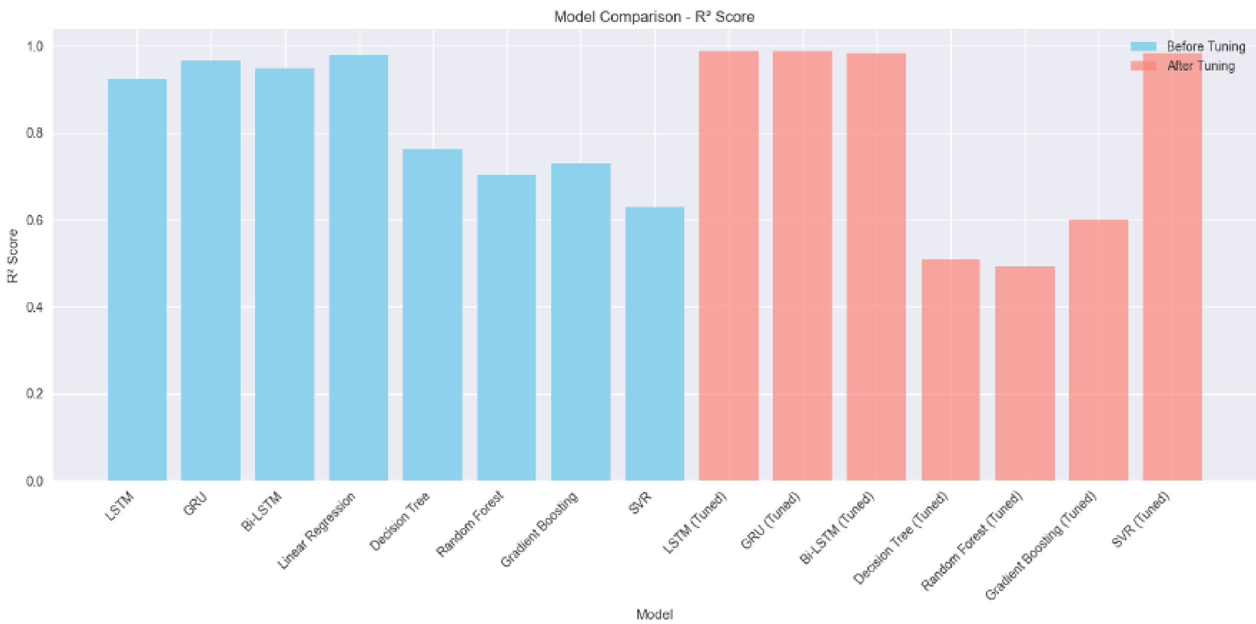

Bi-LSTM (Tuned) - Actual vs Predicted (After Tuning)
Actual
Predicted
Price
0.7
0.6
0.5
0.4
0.3
Time
0
100
200
300
400
500
600


ARIMA Model - Actual vs Predicted
Actual
ARIMA Predictions
Close Price
45000
40000
35000
30000
25000
20000
15000
2022-04
2022-07
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01
Date


SARIMA Model - Actual vs Predicted
Actual
SARIMA Predictions
Close Price
50000
45000
40000
35000
30000
25000
20000
15000
2022-04
2022-07
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01
Date


Model Comparison - RMSE
Before Tuning
After Tuning
Root Mean Squared Error
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
LSTM
GRU
Bi-LSTM
Linear Regression
Decision Tree
Random Forest
Gradient Boosting
SVR
LSTM (Tuned)
GRU (Tuned)
Bi-LSTM (Tuned)
Decision Tree (Tuned)
Random Forest (Tuned)
Gradient Boosting (Tuned)
SVR (Tuned)
Model


Model Comparison - MAPE
Before Tuning
After Tuning
Mean Absolute Percentage Error
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
LSTM
GRU
Bi-LSTM
Linear Regression
Decision Tree
Random Forest
Gradient Boosting
SVR
LSTM (Tuned)
GRU (Tuned)
Bi-LSTM (Tuned)
Decision Tree (Tuned)
Random Forest (Tuned)
Gradient Boosting (Tuned)
SVR (Tuned)
Model


Model Comparison - R² Score
Before Tuning
After Tuning
R² Score
0.0
0.2
0.4
0.6
0.8
1.0
LSTM
GRU
Bi-LSTM
Linear Regression
Decision Tree
Random Forest
Gradient Boosting
SVR
LSTM (Tuned)
GRU (Tuned)
Bi-LSTM (Tuned)
Decision Tree (Tuned)
Random Forest (Tuned)
Gradient Boosting (Tuned)
SVR (Tuned)
Model