Journal of Science Research and Reviews
PRINT ISSN: 1595-9074
E-ISSN: 1595-8329
DOI: https://doi.org/10.70882/josrar.2025.v2i1.34
Homepage: https://josrar.esrgngr.org
Original Research Article

Sentiment-Driven and Economic Indicators for Bitcoin Price Forecasting: A Hybrid Time Series Model

***Kabo, Ibrahim G., Obunadike, Georgina N. and Samaila, Nuruddeen A.**

Department of Computer Science, Federal University Dutsin-Ma, Katsina State, Nigeria
*Corresponding Author's email: igkabo@fudutsinma.edu.ng

KEYWORDS
Bitcoin price prediction,
ARIMA,
LSTM,
Sentiment analysis,
Economic indicators.

CITATION
Kabo, I. G., Obunadike, G. N., & Samaila, N. A. (2025). Sentiment-Driven and Economic Indicators for Bitcoin Price Forecasting: A Hybrid Time Series Model. *Journal of Science Research and Reviews*, *2*(1), 99-107. https://doi.org/10.70882/josrar.2025.v2i1.34

ABSTRACT
Bitcoin, the leading cryptocurrency, has gained significant attention due to its high volatility and potential economic impact. Traditional financial forecasting models struggle to accurately predict Bitcoin prices due to its sensitivity to various factors, including market sentiment and macroeconomic conditions. Existing models primarily rely on historical price data, often neglecting external influences such as public sentiment and economic indicators like Gross Domestic Product (GDP). To address these limitations, this study explores a hybrid approach that integrates Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) models with sentiment analysis and GDP data to enhance Bitcoin price prediction accuracy. The study evaluates the predictive capabilities of these models under different scenarios. When trained on Bitcoin price data combined with sentiment analysis and GDP data, the ARIMA model achieved a Mean Absolute Error (MAE) of 2081.66, Root Mean Square Error (RMSE) of 2518.35, and an R-squared value of 0.9143. In comparison, when trained on Bitcoin data alone, it exhibited lower accuracy. The LSTM model demonstrated superior performance, achieving an MAE of 1253.24, RMSE of 1717.65, and an R-squared value of 0.9602 when incorporating sentiment and GDP data, significantly outperforming its standalone counterpart. The results highlight the effectiveness of integrating sentiment analysis and GDP data in cryptocurrency price prediction, demonstrating that hybrid models provide greater forecasting accuracy than traditional approaches. This study offers a robust framework for financial time series forecasting, aiding investors, analysts, and policymakers in making more informed decisions in the cryptocurrency market.

INTRODUCTION

The emergence of Bitcoin as the most popular cryptocurrency has revolutionized the global financial landscape by providing a decentralized, transparent, and borderless alternative to traditional financial systems. Its popularity has increased dramatically as a store of value, an investment vehicle, and a medium of exchange, but its inherent volatility presents serious difficulties for investors, policymakers, and researchers. Precisely forecasting Bitcoin prices is essential for making well-informed decisions, reducing risk, and creating strong trading strategies. A complex interplay of factors, including supply and demand dynamics, market sentiment, technological advancements, and macroeconomic conditions, has made market sentiment a major driver of cryptocurrency price movements. Sentiment analysis, a technique for extracting and quantifying opinions from textual data, has proven effective in capturing these psychological and emotional factors that shape market behavior. In addition to sentiment, macroeconomic indicators like GDP provide valuable insights into the broader economic environment in which Bitcoin operates (Mai et al., 2018). The proliferation of social media platforms, news outlets, and online forums has created an ecosystem where public opinion significantly impacts market trends. Incorporating macroeconomic indicators like GDP into forecasting models provides a more comprehensive understanding of the forces influencing Bitcoin's price dynamics, even though it is frequently regarded as an asset class separate from traditional financial systems. For instance, during times of economic uncertainty or recession, Bitcoin has been perceived as a safe haven asset and a hedge against inflation, which drives its demand and price (Walther et al., 2019).

Because they can capture linear dependencies in sequential data, traditional statistical models like the Autoregressive Integrated Moving Average (ARIMA) have been utilized extensively for time series forecasting. These models, however, frequently have trouble capturing the intricate patterns and non-linear interactions seen in bitcoin markets. However, because of their ability to identify long-term and non-linear dependencies in data, machine learning models—in particular, deep learning architectures like Long Short-Term Memory (LSTM) networks—have shown great promise in financial forecasting (Parekh, 2022). LSTM networks are a great option for predicting bitcoin prices since they excel at processing time series data with sequential dependencies. This model remembers earlier long-term time-series data and provides autonomous control of the cell state to keep beneficial attributes while eliminating unnecessary ones (Ajik et al, 2023). They are also used to forecast continuous results (Olanrewaju et al, 2023).

This study presents a hybrid strategy that harnesses the capabilities of ARIMA and LSTM models while incorporating sentiment analysis with GDP data. By including sentiment analysis and GDP as additional variables, the model reflects the multi-dimensional drivers of Bitcoin price changes. Sentiment ratings are obtained from textual data using natural language processing techniques, whereas GDP data represents macroeconomic conditions. This integrated approach allows a full examination of Bitcoin's price determinants, including both market sentiment and broader economic issues.

Because of its high volatility and increasing economic significance, the forecasting of Bitcoin prices has become a crucial area of research. The majority of early studies concentrated on statistical models for time series forecasting, such as the Autoregressive Integrated Moving Average (ARIMA) model, which has been widely used in financial applications because it can model linear dependencies in sequential data (Saleti et al., 2024). However, because of its significant limitations when dealing with non-linear relationships and complex market dynamics, which are frequently observed in the cryptocurrency market, researchers have turned to more sophisticated methods, such as machine learning and deep learning models.

Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, are particularly well-suited for financial applications because they can learn long-term dependencies and non-linear patterns in sequential data (Lotfi and Vishwanath, 2020). Several studies have shown that LSTM models are more accurate than traditional methods at predicting cryptocurrency prices; for example, McNally et al. (2018) compared ARIMA and LSTM models for Bitcoin price forecasting and found that LSTM outperformed ARIMA in terms of accuracy, highlighting the potential of deep learning in capturing the intricate dynamics of cryptocurrency markets.

Cryptocurrency prices have also been found to be significantly influenced by market mood. Sentiment analysis measures public sentiment by removing subjective viewpoints from textual data. Mai et al. (2018) investigated how sentiment on social media affected the value of Bitcoin and discovered a significant relationship between price fluctuations and sentiment polarity. In a similar vein, Mule (2024) emphasized how well sentiment research captures market changes and enhances forecasting models. Predictive models have been demonstrated to perform better when sentiment data is incorporated into them since it reflects current market attitudes and behavioral trends.

Financial markets are significantly shaped not just by mood but also by macroeconomic statistics like GDP. Even though cryptocurrencies like Bitcoin are sometimes seen as separate from established financial institutions, market dynamics and investor behavior may be impacted by the state of the economy. According to Walther et al. (2019), who looked at the connection between Bitcoin and macroeconomic variables, monetary policy, GDP growth, and inflation all have an indirect impact on Bitcoin pricing. A wider context is provided by the incorporation of macroeconomic indicators into forecasting models, enabling more thorough examinations of price determinants.

In financial forecasting, hybrid models that combine cutting-edge machine-learning approaches with conventional statistical methods have become more popular. In order to overcome each approach's shortcomings, these models seek to integrate the best features of each strategy. Albeladi et al (2023), for instance, suggested a hybrid ARIMA-LSTM model for stock price prediction and showed that it performed better than solo models. Hybrid methodologies have also been used to bitcoin markets, with academics incorporating sentiment analysis and macroeconomic variables into forecasting systems. Hybrid models, which provide a reliable solution for precise forecasts, capture the multifaceted factors influencing Bitcoin prices by utilizing a variety of data sources.

The quality and reliability of sentiment data, which can be noisy and manipulable, and the selection and preprocessing of macroeconomic variables, which need to be carefully considered to ensure their relevance and impact, are two issues that still need to be addressed in order to develop models that are both accurate and interpretable. These issues persist despite these advancements in the integration of sentiment analysis and economic indicators with predictive models.

By putting forth an improved ARIMA and LSTM model that incorporates sentiment analysis and GDP data for Bitcoin price forecasting, this work expands on the body of previous knowledge. This research attempts to remedy the shortcomings of current models while using the distinctive drivers of cryptocurrency marketplaces by fusing the advantages of conventional and cutting-edge methodologies. This method adds to the expanding corpus of research examining the relationship between time series forecasting, economic indicators, and sentiment analysis, providing fresh perspectives and useful ramifications for those involved in the bitcoin space.

MATERIALS AND METHODS

Methodology and tool selection criteria selected is an important factor to the performance of any algorithm (Ogwueleka and Obunadike, 2012, Obunadike et al, 2015). The study used a quantitative research design to predict Bitcoin prices using deep learning techniques as well as traditional time series models. The study used GDP Data and Sentiment Analysis to predict the price of Bitcoin by integrating the LSTM and ARIMA model. The steps in Figure 1 are used to further carry out this prediction.

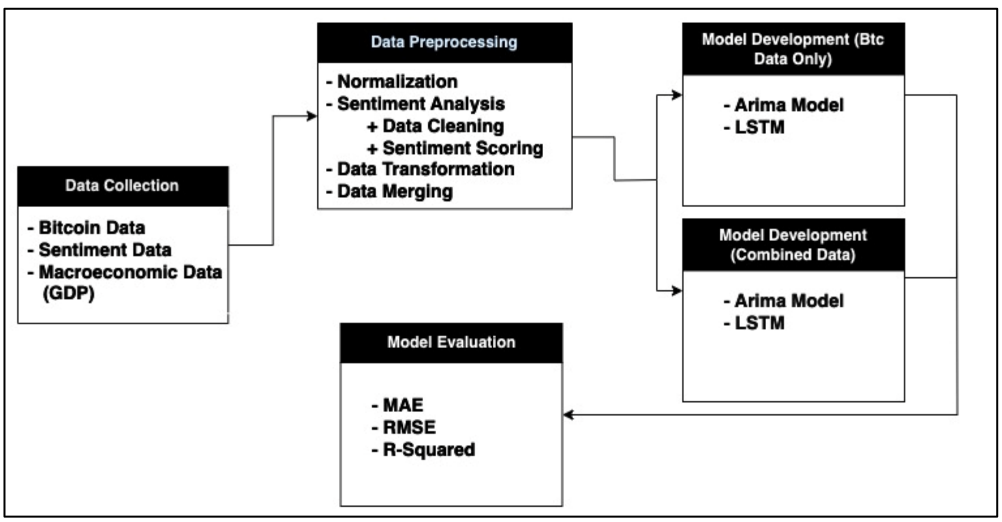

Figure 1: Model Development Steps

Data Collection

From January 2020 to November 2024, Yahoo Finance, a trustworthy financial data platform, provided historical Bitcoin price data. Table 1 summarizes some of the data's fundamental characteristics.

Table 1: Bitcoin Dataset Attributes

S/N	Column Name	Attribute (Data Type)
1	Date	Date
2	Adj. Close	Double
3	Close	Double
4	High	Double
5	Low	Double
6	Open	Double
7	Volume	Double

From January 2020 to November 2024, economic indicators, specifically GDP growth rates, are sourced from Kaggle. The initial data contains other macroeconomic data, such as inflation rates, unemployment rates, etc. Only the GDP rate will be used for this research, so other columns were deleted. Sentiment data is extracted from X (formerly Twitter) using Tweepy for Twitter, which generates sentiment scores based on relevant keywords and hashtags. Ten tweets are extracted for each day beginning on January 1, 2021, to September 30, 2024, and are then classified as positive, negative, or neutral.

Data Preprocessing

Data preprocessing is an important stage in every machine-learning process. This technique guarantees a model's quality and consistency (Iliyasu et al., 2023). To maintain consistent scales, Bitcoin price data is normalized using Min-Max scaling, which transforms the numbers into a range of 0 to 1. This helps to stabilize the training process for deep learning models. Social media postings are preprocessed to remove punctuation, stop words, and emoticons. To minimize text complexity, procedures such as tokenization and lemmatization are used. The Textblob library generates sentiment scores for each post, which might be favorable, negative, or neutral. The aggregate daily sentiment scores are then computed. ARIMA models rely on stationary data, hence the augmented Dickey-Fuller (ADF) test is used to determine stationarity. If non-stationary, differencing is used until stationarity is attained. To meet the input requirements for time series prediction, the LSTM model transforms data into three-dimensional arrays.

Model Development

The Autoregressive Integrated Moving Average (ARIMA) model was chosen for its effectiveness in time series forecasting. The parameter for (p,d,q) is (1,1,0). The LSTM model consists of three layers: the input layer, which accepts time-series data in a sequential format, the LSTM layers (two LSTM layers with dropout are used to prevent overfitting), and the Dense Layer, which is a fully connected layer with a single neuron as the output layer, predicting the Bitcoin price for the next time step. To improve the predictive accuracy of each model, a hybrid model is created for both ARIMA and LSTM, with daily sentiment scores and macroeconomic indicators added as extra features.

Model Evaluation

To assess model performance, several evaluation metrics are used:

Mean Absolute Error (MAE): MAE is the average of the absolute differences between the measured and true values. It's a linear score that treats all errors equally. The formula is represented in equation 1.

$$MAE = \frac{1}{n}\sum_{i=1}|yi - yi| \quad (1)$$

Root Mean Square Error (RMSE): RMSE is the square root of the average squared differences between the measured and true values. It's a quadratic scoring rule that gives more weight to larger errors. The formula is represented in equation 2.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}(yi - yi)^2} \quad (2)$$

R-Squared (R^2): R-squared measures how much of the variability in the dependent variable is explained by the independent variables.

RESULTS AND DISCUSSION

This study compared the performance of two forecasting models, ARIMA and LSTM, in predicting Bitcoin prices under two scenarios: (1) utilizing only historical Bitcoin price data, and (2) including sentiment analysis and GDP data as additional predictors. The findings show that adding emotion and economic variables greatly enhances the forecast accuracy of both models.

Result from Sentiment Analysis

After Sentiment Analysis was carried out using Textblob Library, the result obtained is captured in Table 2.

Table 2: Sentiment Analysis Result

Overall Sentiment	coEunt
Positive	7029
Neutral	5236
Negative	1425

To determine whether the data is positive or negative, the library calculates sentiment scores for each column in the data frame. Because there are 10 tweets per day, the average sentiment score for each day is calculated.

A word cloud depicts the most common words found in a corpus. Figure 2 depicts a Wordcloud containing the most frequently appearing words in the corpus obtained from training the model.

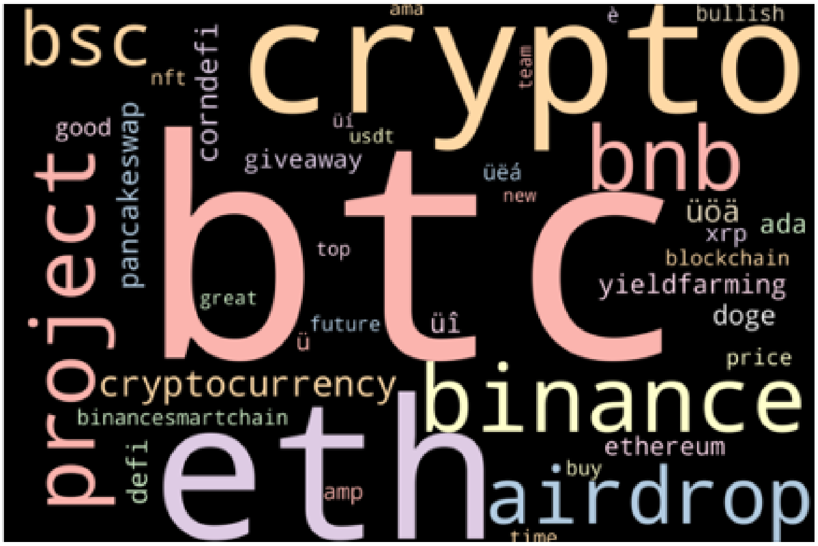

Figure 2: Wordcloud detailing the most appearing words (Source: Author's Result)

ARIMA Model Performance

The model was initially trained using the Arima model without Sentiment and Macroeconomic GDP data. Following that, sentiment and macroeconomic GDP statistics are added to the dataset. Table 3 shows the obtained results, and Figure 3 depicts them graphically. These findings show that incorporating external data sources allows the model to capture more explanatory variables, improving its ability to predict Bitcoin price movements.

Table 3: Results obtained from Training ARIMA Model

	MAE	RMSE	R-Squared
ARIMA alone	2567.98	2947.10	0.8827
ARIMA with other data	2081.66	2518.35	0.9144

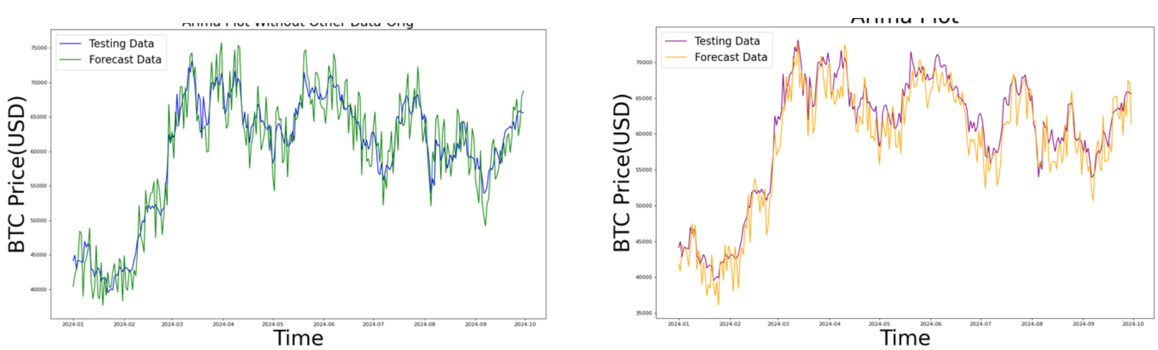

Figure 3: Result of Bitcoin Prediction using ARIMA

LSTM Model Performance

The LSTM model outperformed the ARIMA model by learning complex, non-linear patterns in the data. The model was trained using only Bitcoin price data, as well as Bitcoin data combined with sentiment and macroeconomic data. The results are summarized in Table 4, and a graphical representation of the results is captured in Figure 4. These results highlight the LSTM model's strength in incorporating diverse data inputs to enhance forecasting.

Table 4: Results obtained from Training LSTM Model

	MAE	RMSE	R-Squared
LSTM alone	1410.03	1821.04	0.8924
LSTM with other data	1253.24	1717.65	0.9602

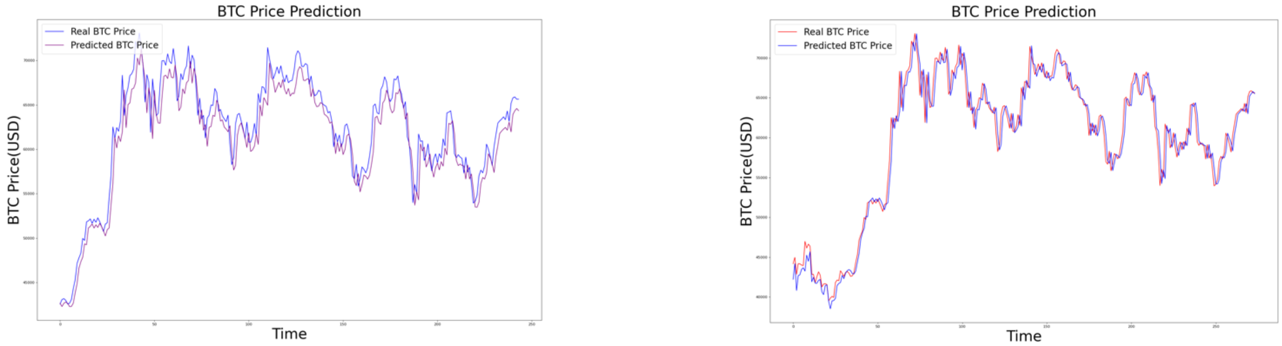

Figure 4: Result of Bitcoin Prediction using LSTM

Discussion

The combination of sentiment analysis and GDP data significantly improved the predicted accuracy of both ARIMA and LSTM models. This conclusion emphasizes the significance of external data sources in capturing the multidimensional elements that influence Bitcoin values. Sentiment research represents market players' psychological and behavioral factors, which are especially important in the bitcoin market, where speculation and social media play major roles. GDP data, on the other hand, depicts the larger economic environment, connecting Bitcoin's performance to macroeconomic trends and investor behavior.

Comparative Analysis of ARIMA and LSTM

In every situation, the LSTM model performed better than the ARIMA model, especially when external data sources were taken into account. This outcome is consistent with earlier studies that demonstrate LSTM's capacity to represent intricate, non-linear interactions and long-term dependencies in time series data. Although ARIMA does a good job of capturing short-term linear patterns, it is less appropriate for the complex and volatile nature of cryptocurrency markets due to its shortcomings in handling non-linear dynamics.

The benefits of combining deep learning methods with a variety of data sources are demonstrated by the hybrid LSTM model's enhanced performance. The hybrid technique captures a wider variety of price determinants, leading to more accurate and dependable forecasts, as evidenced by the large decrease in error metrics (MAE and RMSE) and the higher R-squared values as evident in Figure 5.

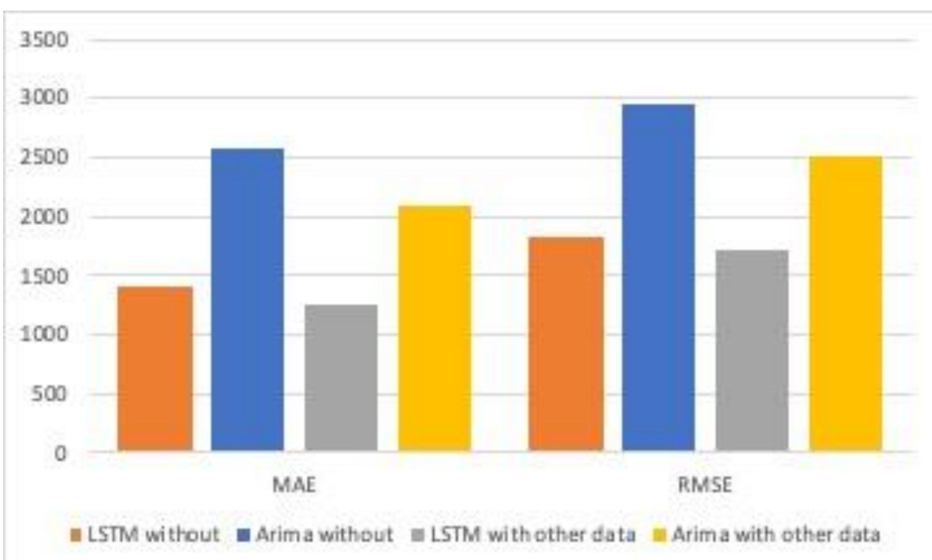

Figure 5: Comparison of results from both models using LSTM and Arima

Practical Implications

The results of this research have broad implications for cryptocurrency experts, investors, and legislators. Forecasting models that incorporate sentiment research and economic data offer a more thorough comprehension of the fluctuations of the Bitcoin price. This strategy can

JOSRAR 2(1) JAN-FEB 2025 99-107

help investors make better decisions by providing information about market trends and lowering the risks related to price volatility. Policymakers can improve regulatory frameworks and promote market stability by having a better understanding of how economic factors and Bitcoin prices interact.

Limitations and Future Research

Despite its promising results, this study has certain limitations. The sentiment data used in the analysis was derived from selected social media platforms and news sources, which may not fully capture the diversity of opinions and sentiments influencing Bitcoin prices. Additionally, the GDP data, while representative of macroeconomic conditions, may not account for other relevant factors such as inflation, monetary policy, or geopolitical events.

Future research could address these limitations by incorporating a broader range of sentiment and economic indicators, exploring alternative data sources such as blockchain analytics or real-time transaction data, and testing the hybrid model in different cryptocurrency markets. Furthermore, the scalability and generalizability of the proposed framework could be evaluated across longer time horizons and varying market conditions.

Table 5: Comparison of research model perfomance

Author	Model	Performance
Our Work	ARIMA ONLY	MAE of 2567.98, RMSE of 2947.10, R-Square of 0.8827
	ARIMA COMBINED	MAE of 2081.66, RMSE of 2518.35, R-Square of 0.9144
	LSTM ONLY	MAE of 1410.03, RMSE of 1821.04, R-Square of 0.8924
	LSTM COMBINED	MAE of 1253.24, RMSE of 1717.65, R-Square of 0.9602
Berlilana and Mu'amar, 2024	ARIMA	RMSE of 0.0 MAE of 2.308e-215
	LSTM	RMSE of 0.000219 MAE of 0.000218
jun Gu et al, 2024	developed a pre-trained NLP model known as FinBERT, incorporated the sophisticated Long Short-Term Memory (LSTM) architecture,	accuracy of 0.955 at 77 epochs, a testing loss of 0.00083, an MAE of 173.67, and a MAPE of 0.045,
Kasture et al., 2024	hybrid RNN-LSTM	mean absolute error (0.036) mean squared error (0.021) root mean square error (0.046)
Rao et al, 2023	Random Forest Regression (RF), Support Vector Regression (SVR), Autoregressive Integrated Moving Average (ARIMA), and their extended versions with exogenous variables (ARIMAX)	

CONCLUSION

This study demonstrates the significant improvements in forecasting Bitcoin prices through a hybrid approach that integrates sentiment analysis, economic indicators like GDP, and advanced time series models, such as ARIMA and LSTM. The results highlight the importance of incorporating diverse data sources beyond historical Bitcoin prices to better capture the underlying factors driving market dynamics, such as investor sentiment and broader economic conditions. The LSTM model, in particular, outperformed the ARIMA model, showcasing its ability to effectively model non-linear dependencies and long-term relationships in the highly volatile cryptocurrency market. These findings suggest that hybrid models, which combine traditional statistical methods with machine learning, offer a more comprehensive and accurate forecasting framework. While this research contributes valuable insights, future studies could build on these findings by incorporating additional data sources, such as real-time transaction data and other macroeconomic indicators, to further enhance predictive accuracy. Moreover, exploring alternative deep learning architectures and extending the model to other cryptocurrencies could help assess its scalability and generalizability, making it a potentially invaluable tool for investors, analysts, and policymakers navigating the complexities of cryptocurrency markets.

REFERENCES

Ajik, E. D., Obunadike, G. N., & Echobu, F. O. (2023). Fake News Detection Using Optimized CNN and LSTM Techniques. In Journal of Information Systems and Informatics (Vol. 5, Issue 3, pp. 1044–1057). Asosiasi Perguruan Tinggi Informatika dan Komputer (APTIKOM) Sumsel. https://doi.org/10.51519/journalisi.v5i3.548

Albeladi, Khulood & Zafar, Bassam & Mueen, Ahmed. (2023). Time Series Forecasting using LSTM and ARIMA. International Journal of Advanced Computer Science and Applications. 14. https://doi.org/10.14569/IJACSA.2023.0140133

Berlilana, W, and Mu'amar, A. (2024). "Time Series Analysis of Bitcoin Prices Using ARIMA and LSTM for Trend Prediction," J. Digit. Mark. Digit. Curr., vol. 1, no. 1, pp. 84-102.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time Series Analysis: Forecasting and control* (5th ed.). Wiley. https://doi.org/10.1002/9781118619193

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation, 9*(8), 1735–1780. MIT PRESS. https://doi.org/10.1162/neco.1997.9.8.1735

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Iliyasu, U., Obunadike, G. N., & Jiya, E. A. (2023). Rainfall Prediction Models for Katsina State, Nigeria: Machine Learning Approach. In International Journal of Science for Global Sustainability (Vol. 9, Issue 2, pp. 151–157). Federal University Gusau. https://doi.org/10.57233/ijsgs.v9i2.473

jun Gu, W., hao Zhong, Y., zun Li, S., song Wei, C., ting Dong, L., yue Wang, Z., & Yan, C. (2024). Predicting Stock Prices with FinBERT-LSTM: Integrating News Sentiment Analysis. In Proceedings of the 2024 8th International Conference on Cloud and Big Data Computing (pp. 67–72). ICCBDC 2024: 2024 8th International Conference on Cloud and Big Data Computing. ACM. https://doi.org/10.1145/3694860.3694870

Kasture P, Shirsath K (2024) Enhancing Stock Market Prediction: A Hybrid RNN-LSTM Framework with Sentiment Analysis. Indian Journal of Science and Technology 17(18): 1880-1888. https://doi.org/10.17485/IJST/v17i18.466

Lotfi, Ali & Vishwanath, Sriram. (2020). Long Short-Term Memory Spiking Networks and Their Applications. 10.48550/arXiv.2007.04779.

Mai, F., Shan, Z., Bai, Q., Wang, X., & Chiang, R. H. L. (2018). How does social media impact Bitcoin's value? A test of the silent majority hypothesis. *Journal of Management Information Systems, 35*(1), 19-52. https://doi.org/10.1080/07421222.2018.1440774

McNally, S., Roche, J., & Caton, S. (2018). Predicting the Price of Bitcoin Using Machine Learning. In 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP) (pp. 339–343). 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP). IEEE. https://doi.org/10.1109/pdp2018.2018.00060

Mule, V. (2024). Survey on Bitcoin Price Prediction using Machine Learning. In International Journal for Research in Applied Science and Engineering Technology (Vol. 12, Issue 1, pp. 1181–1182). International Journal for Research in Applied Science and Engineering Technology (IJRASET). https://doi.org/10.22214/ijraset.2024.58047

Obuandike Georgina N., Audu Isah and John Alhasan (2015), "Analytical Study of Some Selected Classification Algorithms in WEKA Using Real Crime Data" International Journal of Advanced Research in Artificial Intelligence(IJARAI), 4(12). http://dx.doi.org/10.14569/IJARAI.2015.041207.

Ogwueleka, Francisca and Obunadike, Georgina. (2012). Methodology and tool selection criteria in data mining. Global Advanced Research Journal of Engineering, Technology and Innovation. 1. 131-137.

Olanrewaju, Mary and Luka, Stephen and Echobu, Faith. (2023). Prediction of Forex Prices on USD/NGN Using Deep Learning (LSTM and GRU) Techniques. Journal of Information Systems and Informatics. 5. 1609-1622. https://doi.org/10.51519/journalisi.v5i4.606

Parekh, R., Patel, N. P., Thakkar, N., Gupta, R., Tanwar, S., Sharma, G., Davidson, I. E., & Sharma, R. (2022). DL-GuesS: Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction. In IEEE Access (Vol. 10, pp. 35398–35409). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2022.3163305

Rao, J., Zhang, Q., Ke, Z., Liu, S., & Liu, X. (2023). Integrating Textual Analytics with Time Series Forecasting Models: Enhancing Predictive Accuracy in Global Energy and Commodity Markets. In Innovations in Applied Engineering and Technology (pp. 1–7). Global Science Publishing Pty. Lte. https://doi.org/10.62836/iaet.v2i1.265

Saleti, Sumalatha & Panchumarthi, Lovely & Kallam, Yogeshvar Reddy & Parchuri, Lavanya & Jitte, Shilpa. (2024). Enhancing Forecasting Accuracy with a Moving Average-Integrated Hybrid ARIMA-LSTM Model. SN Computer Science. 5. https://doi.org/10.1007/s42979-024-03060-4

Walther, Thomas; Klein, Tony; Bouri, Elie (2019). Exogenous drivers of Bitcoin and Cryptocurrency volatility – A mixed data sampling approach to forecasting. Journal of International Financial Markets, Institutions and Money, Volume 63, 101133, ISSN 1042-4431, https://doi.org/10.1016/j.intfin.2019.101133.