Predicting Bitcoin price movement through Sentiment Analysis: A Comprehensive Study

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ABSTRACT

The people's feelings in tweets can affect on the direction of Bitcoin price. The study aimed to figure out how much Twitter posts affect the price movement of Bitcoin. It was tried to find accurate prediction models through a Sentiment Analysis (SA) that can predict these changes. Data collection was included real-time Twitter data from January 31, 2023, to June 6, 2023, focusing on English tweets containing the keyword "bitcoin". These data were paired with hourly Bitcoin price data, covering open, high, low, close, and volume values. Two pre-trained RoBERTa models (Tweetnlp and BERTweet) were used to perform SA on the collected tweets. Three neural network models (Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (BiLSTM)) were explored and evaluated at different temporal granularities ranging from 2 hours to 17 hours. The findings showed that combining SA could improve prediction accuracy in a specific time horizon. The highest accuracy (90.3%) was achieved by a 2-layer GRU incorporating Tweetnlp sentiment analysis at a 16-hour lag. The research offers valuable insights into the role of SA in understanding and potentially predicting fluctuations in Bitcoin prices, highlighting its significance in the realm of cryptocurrency analysis. Future research could explore additional factors affecting the connection between social media sentiment and Bitcoin price.

CCS CONCEPTS

• **Computing methodologies → Neural networks**.

KEYWORDS

Sentiment Analysis, BERT, RoBERTa LSTM, BiLSTM, GRU, Bitcoin Price Movement Prediction

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1 INTRODUCTION

Bitcoin, a groundbreaking decentralized digital asset, facilitates peer-to-peer transactions via blockchain technology, eliminating the need for central authorities or trusted financial intermediaries.[27] Since its inception in 2009, Bitcoin's remarkable volatility has captured significant attention, offering lucrative opportunities for digital trading. By November 2021, Bitcoin's market capitalization soared to $1.28 trillion, with each bitcoin priced at $67,617.02, marking an extraordinary ascent from its initial worthlessness in 2008. However, the price of Bitcoin is predominantly influenced by the fundamental dynamics of supply and demand interactions [23], necessitating precise forecasting to equip traders with a competitive edge. The prediction of Bitcoin prices has emerged as a prominent research area worldwide. Researchers have employed various machine learning and deep learning algorithms, including Gate Recurrent Unit (GRU), Neural Network (NN), and Long Short-term Memory (LSTM), to predict and analyze factors affecting Bitcoin prices.[14][26] Furthermore, price volatility is significantly driven by investor behavior, influenced by online information searches via social networks and news coverage, impacting Bitcoin's price in both the short and long term.[6] Among micro-blogging platforms, Twitter stands out as one of the most ubiquitous sources of cryptocurrency information. Not only does Twitter provide timely updates on Bitcoin, but it also serves as a rich source of emotional signals, with investors frequently expressing their sentiments. A promising approach involves utilizing sentiment scores derived from microblogs, news, or blogs corresponding to the same period as the price values.[4][11] Several studies have demonstrated correlations between cryptocurrency price movements and social media sentiment, highlighting the potential of Sentiment Analysis(SA) techniques for price prediction.[17][5] Analyzing opinions expressed on cryptocurrency social media platforms may facilitate the prediction of price fluctuations. In line with these studies, we employ SA methods to forecast Bitcoin price movements. Traditionally, SA techniques have relied on complex rules. The widely used Valence Aware Dictionary and Sentiment Reasoner (VADER) method is commonly used for analyzing social media posts. [20] However, traditional methods like VADER may struggle to capture linguistic nuances. Recent advancements in Natural Language Processing (NLP), such as RoBERTa, offer promise.[24][1][30] RoBERTa is a pre-trained transformer model on a massive dataset that excels at understanding context and generalizing across natural language tasks. Several fine-tuned versions of RoBERTa, including those specifically tailored for short messages (like Tweets) and sentiment analysis, have been introduced to demonstrate its effectiveness in this area. [1][9]. In this study, we focus on two popular RoBERTa variants trained on large Twitter datasets introduced by [1] and [9]. While each model has been utilized in a few studies, no prior work has directly compared their effectiveness. This study aims to investigate whether incorporating RoBERTa-derived SA can significantly enhance the accuracy of Bitcoin price movement prediction models. Furthermore, the study seeks to compare the performance of prediction models that incorporate sentiment factors with those that do not, and to determine the optimal time lag of Twitter data batches to improve prediction accuracy.

2 BACKGROUND AND RELATED WORKS

The following section gives an overview of SA background, followed by recent work on cryptocurrency price prediction. The methods combining both areas are reviewed in continuation.

2.1 Sentiment analysis background

SA is the task of identifying and extracting opinions, attitudes, and sentiments expressed from textual content toward entities, including people, events, goods, and subjects. In general, SA techniques can be categorized into lexicon-based and machine learning (ML) approach.[13] Lexicon-based approach makes use of certain words or phrases and associated sentiment scores to compare with the text being classified to determine a final polarity score. VADER is a popular lexicon-based SA method that requires no training. It's based on rule-matching, which assigns sentiment scores based on the input text using linguistic patterns.[20] However, SA of Twitter data faces many challenges, mainly due to the short length of tweets and the frequent use of informal and irregular words.[12] As a result, the lexicon-based approach has limitations in capturing the context-dependent nature of sentiment and all irregular words or expressions. In recent years, one of the state-of-the-art methods to analyze the sentiment is the Bidirectional Encoder Representations from Transformers (BERT) method. This powerful technique enhances context understanding and offers a pre-train model that is simple to modify for a range of downstream tasks. [25] shows that the BERT model outperformed other models including Linear Support Vector Classifier, Ensemble Method, Multinomial Naive Bayes, BiLSTM, and Random Forest with an impressive accuracy of 86%. Similar to the research [28], the BERT model demonstrated superior performance with an accuracy of 92%, compared to the conventional ML algorithms and LSTM model.

2.2 Time Series Forecasting for Cryptocurrencies

This section explores time-series forecasting methods used specifically for cryptocurrency prices. According to [21], there are two main time-series forecast approaches. The first approach with pure models relies solely on historical price data for prediction. Examples of pure models are Autoregressive Integrated Moving Average [29] and Generalized Autoregressive Conditional Heteroskedasticity (GARCH).[7] Some papers present that these models could be used for cryptocurrency price prediction.[15] However, they are more appropriate for univariate and stationary time-series data. Cryptocurrency price, or Bitcoin price is highly volatile and non-stationary, which we demonstrate in the statistical analysis section. This is why Yiquing Hua finds that the LSTM implementation outperforms the ARIMA model for Bitcoin price prediction.[19] In contrast, deep learning (DL) approaches can leverage the inherent non-linearity and non-stationarity of cryptocurrency data, leading to superior forecasting performance. Various types of ML and DL models have been applied to forecast cryptocurrency prices, ranging from simple to high complex.[16] For instance, [2] employed ML models to predict Bitcoin movement based on a large dataset of 24 variables that includes exchange rates, interest rates, macroeconomic variables, 13 cryptocurrencies and four auxiliary variables. Their results show that the traditional logistic regression model outperformed both a linear Support Vector Machine (SVM) and a Random Forest (RF) algorithm, achieving an accuracy of 66%. However, the trend in cryptocurrency price prediction has shifted towards DL models, particularly LSTM networks and GRU networks, due to their ability to capture complex relationships in data. Several recent studies, including [10] and [22], have compared the performance of various statistical, ML, and DL approaches for predicting cryptocurrency prices. The findings show that LSTM and GRU achieve the best performance in forecasting the prices of popular cryptocurrencies, including Bitcoin. Similar to the price movement prediction task, the highest accuracy of 54% was achieved by Multi-Layer Perceptron (MLP) Neural Network, compared to other ML models.[5] In addition, these DL models have been found to be effective in capturing sentiment from social media platforms, which can further enhance their predictive capabilities.

2.3 Combining Time Series forecasting with sentiment analysis

Besides the historical price, sentiment scores are considered as an additional input feature to the prediction model (particularly LSTM networks), in several studies, with encouraging results.[8][3] These sentiment scores are often derived from the VADER, TextBlob, or BERT technique. For example, [17] used VADER SA on daily Twitter data, along with three neural network models (BiLSTM, CNN, LSTM) to predict Bitcoin price changes and magnitude at different time lags (1, 3, and 7 days). The findings showed that BiLSTM performed best with an accuracy of 63% over a 3-day time lag. Interestingly, performance is generally worse with a 7-day lag in nearly all cases. Similarly, [3] proposed a hybrid approach that combined SA (VADER and BERT) with various time series forecasting techniques (LSTM, TCNs, D-linear Regression, and Linear Regression). Their results suggested that sentiment derived from BERT improved the price forecast performance and the Linear Regression model performs best in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Furthermore, the research [18] compared the performance of various ML models with and without Twitter sentiment data extracted using RoBERTa and VADER on Twitter data. Overall, the inclusion of sentiment data provides greater performance for most models, with the highest accuracy score of 90% when using the Multi-Modal Fusion with RoBERTa SA. In addition, RoBERTA sentiment consistently displayed higher accuracy compared to VADER. Reviewing past studies shows that it is crucial to understand the relationship between SA and Bitcoin price fluctuations for informed decision-making in trading and investment strategies.

3 METHODS

In the following, we provided a brief overview of our approach to this study. We delve into the specific methodologies of our forecasting algorithms and SA techniques. As visually described in Figure 1, we conduct two scenarios for forecasting the changes in Bitcoin price with and without SA from Twitter data. First of all, both the historical price of Bitcoin and the time-aligned tweets are gathered. For incorporating sentiment expressed from Tweet, the raw tweet dataset is pre-processed using standard NLP techniques to remove the noises. Next, we generate sentiment scores for each tweet through two popular variations of a BERT model for Twitter data that are introduced by [1] and [9]. We group the output into bins of 1-hour intervals based on the corresponding tweets' time stamps. The last step of data pre-processing is to prepare the data so that it can be used as input to various forecasting methods. Finally, we feed the prepared data from two scenarios into our NN models. To predict the price movement, we employ three NN models: LSTM, GRU, and Bidirectional LSTM (BiLSTM).

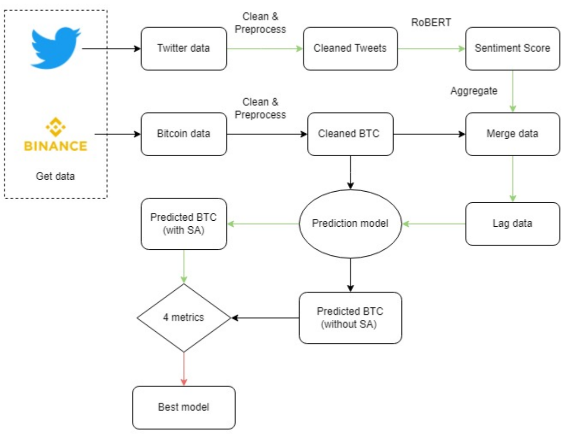


Figure 1: Data Preparation to Forecast by Twitter Sentiment

Attachment 1, shows enhancing Bitcoin price movement forecasting with SA: algorithms, data processing, and analysis in three sections I, II, and III. Table 1 provides an overview of each research question and outlines the steps taken to address them within the methodology. Table 2 provides a comprehensive overview of the data-related aspects mentioned in the methodology.

4 EXPERIMENTAL RESULTS

Here, we present a comprehensive overview of statistical analysis and the results of our experiments in three different datasets, two datasets in sentiment data included and the other without. We built the proposed DL models in Python libraries such as Sklearn, Keras, and TensorFlow. These models were coded using Python 3.9 in Google Colab.

4.1 Results of statistical analysis

When using the Shapiro–Wilk test to examine whether the data is normally distributed, the result reveals that the Bitcoin price does not follow a normal distribution. Additionally, Bitcoin price proves to be a non-stationary time series, based on the ADF test, with ADF statistic of -1.4954 at 1% critical value $ADF_{critical}$ = -3.432 and p = 0.535780, which fails to reject the null hypothesis (p > 0.05).

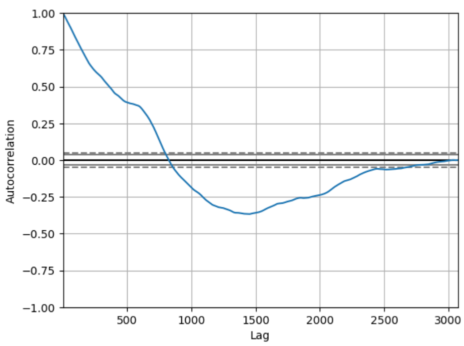
Table 1: Overview of the solutions in the research methodology

Research Questions	Solutions
1. To what extent does sentiment expressed in Tweets significantly impact changes in Bitcoin price movement?	1. Data Collection: Gather historical Bitcoin price data and real-time tweets from Twitter API, filtering English tweets with keywords "btc" or "bitcoin".
	2. Data Pre-Processing: Clean and preprocess tweet data to remove noise and irrelevant elements, then utilize fine-tuned RoBERTa models (TweetNLP (Jose et al, 2022) and BERTweet (Jose et al, 2022)) to extract sentiment scores.
	3. Data Aggregation: Aggregate sentiment scores of tweets within 1-hour intervals, computing mean sentiment scores and a number of polarity sentiments.
	4. Statistical Analysis: Use Pearson's correlation to examine the correlation between sentiment scores derived from RoBERTa models and Bitcoin price movements.
	5. Forecasting Algorithms: Incorporate SA from TweetNLP and BERTweet-based models alongside historical Bitcoin price data into LSTM, GRU, BiLSTM models for predicting price movements.
2. Which prediction model demonstrates the most accurate prediction for Bitcoin price movement?	1. Statistical Analysis: Utilize Augmented Dickey-Fuller (ADF) test of autocorrelation to assess the stationarity
	2. Machine Learning Approach: Train LSTM, GRU, BiLSTM models using historical Bitcoin price data with and without SA from fine-tuned RoBERTa models.
	3. Model Evaluation: Evaluate model performance using accuracy, precision, recall, and F1-score metrics on validation and test sets, comparing predictions with and without sentiment analysis.
1. What is the optimal time that significantly influences the accuracy of Bitcoin price movement?	1. Time-Series Analysis: Identify the limited timeframe for feasible prediction by using autocorrelation. Investigate the impact of sentiment analysis from RoBERTa models on predicting Bitcoin price movements at different time intervals
	2. Data Splitting and Merging: Split data into train, validation, and test sets, merging historical Bitcoin prices with sentiment scores from TweetNLP and BERTweet-based models, exploring lagged features' effects on model performance.
	3. Model Evaluation: Assess model performance with various lag intervals using metrics such as accuracy, precision, recall, and F1-score, determining the time intervals that significantly influence prediction accuracy.

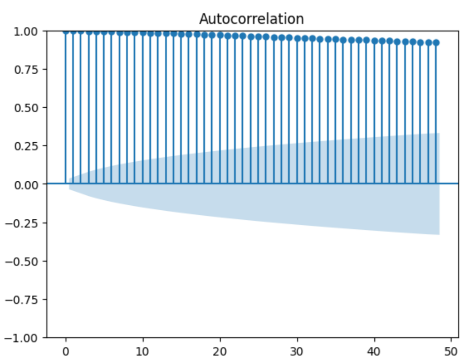
Table 2: Overview of Dataset Aspects and Descriptions

Aspect	Description
Data Source	Historical Bitcoin price data obtained from Binance API Real-time tweets fetched from Twitter API v2 using Tweepy
Time Period	Data collected from 31st January 2023 to 6th June 2023
Bitcoin Price Data	Collected at 1-hour intervals, consisting of open, close, high, low, and volume fields
Twitter Data	Filtered English tweets with keywords "btc" or "bitcoin", collected at 30-second intervals
Raw Twitter Dataset Attributes	- id: Unique identifier for each tweet - created_at: Timestamp of tweet creation - text: Content of the tweet
Data Pre-Processing	Lowercasing and expanding contractions Removing unnecessary parts (URLs, hashtags, etc.) Removing stopwords Lemmatization
Data Cleaning	Removal of noise and irrelevant elements from tweets
Data Aggregation	Aggregating sentiment scores of tweets within 1-hour intervals Computing mean sentiment scores and number of polarity sentiments
Data Splitting and Merging	Merging historical Bitcoin prices and polarity scores from Twitter into a single data source Splitting data into train, validation, and test sets
Introducing Lag	Investigating continuous time lags by hour Shifting merged dataset back by the lag value being tested Introducing lagged datasets including observations for previous days
Features on Dataset	Non-sentiment dataset: closing price and target price movement Sentiment dataset: closing price, positive score, neutral score, negative score, tweet volume, and target price movement

According to the auto-correlation method of historical Bitcoin price in Figure 2a, there is strong positive correlation (nearly 1) for lags up to 500 hours. However, the correlation decreases gradually as the time lag increases, which is shown in the Figure 2b. To identify the optimal time lag for forecasting price movement, this paper focuses on lags from 2 hours to 10 hours.



(a) Autocorrelation in the whole period



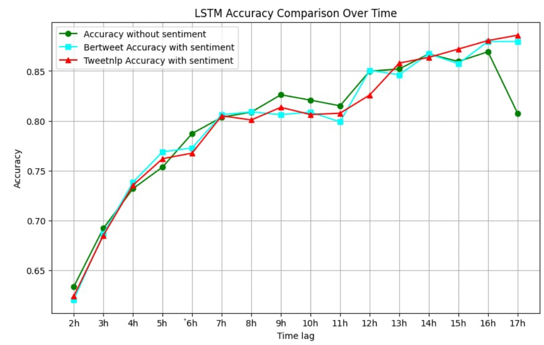
(b) Autocorrelation in 50-hour interval

Figure 2: Autocorrelation analysis of Bitcoin prices

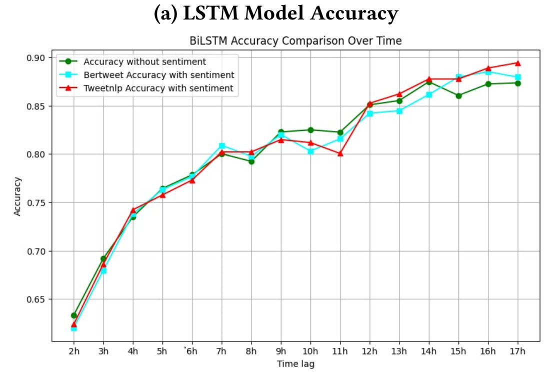
When combining sentiment from Twitter, we have many features in a single time step beyond the closing Bitcoin price, including neutral score, negative score, positive score, and tweet volume. Our objective is to predict the daily price direction of Bitcoin, which is defined as a binary variable: 1 indicates a price decrease, and 0 indicates a price increase. In other words, if the Bitcoin closing price $P_{BTC}[t+n] \geq P_{BTC}[t]$, then $y[t] = 0$ and if $P_{BTC}[t+n] < P_{BTC}[t]$, then $y[t] = 1$, where n is a time lag and $y[t]$ is a target direction variable. To understand the association of all features, we analyze the cross-correlation among multiple features extracted from Twitter data. Overall, neutral scores and the number of neutral tweets exhibit a strong negative correlation with all other sentiment measures (negative score, positive score, number of negative tweets, number of positive tweets) in two datasets with SA.

4.2 Results of price movement prediction

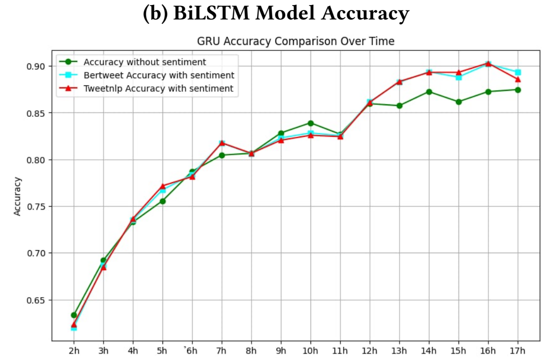
This paper aims to investigate whether the inclusion of Twitter data provides greater performance in our models when trying to forecast Bitcoin price movement. As a result, we compared the performance of three classification models for predicting the direction of Bitcoin price in both scenarios: with and without using sentiment extracted from both RoBERTa models – TweetNLP and BERTweet-based SA. Our timeframe is limited from 2-hour to 17-hour intervals. Although accuracy and F1-score are key performance metrics we should evaluate, the similar values for both suggest that our data is quite well balanced between two classes – increase vs. decrease. Therefore, we will focus on the accuracy results when comparing the model performance. Figure 3 visually compares the accuracy of models in different time lags.



(a) LSTM Model Accuracy



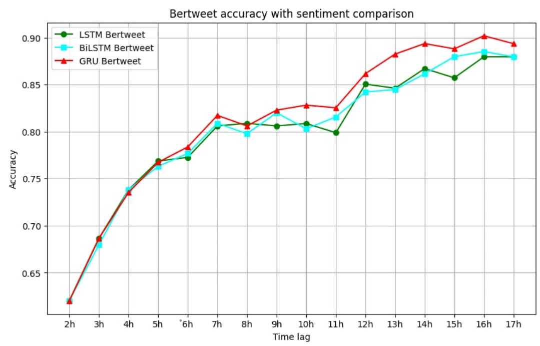
(b) BiLSTM Model Accuracy



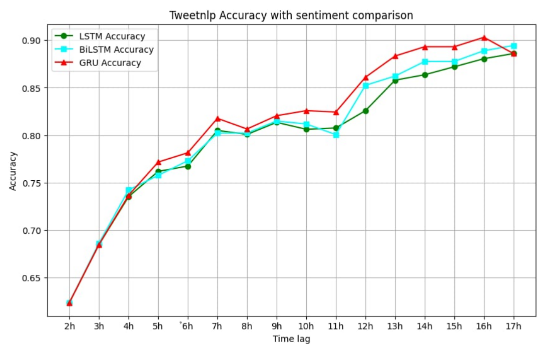
(c) GRU Model Accuracy

Figure 3: Accuracy results in each model

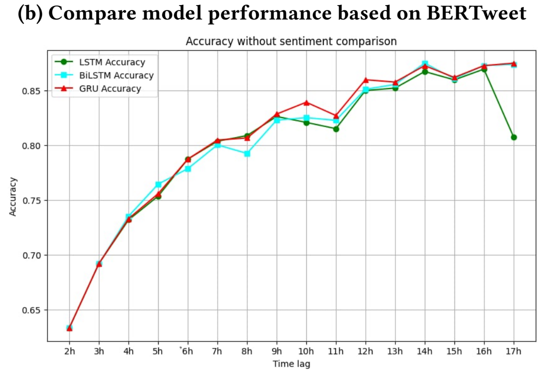
Overall, the accuracy of all three models increases over time. This suggests that all models are better at predicting the price movement in both cases. Interestingly, the model performance without SA achieved higher accuracy over 12 first hours and went lower than the model including sentiment data in 5 last hours. The GRU model outperforms two other models – LSTM and BiLSTM in both cases, which is demonstrated in Figure 4.



(a) Compare model performance based on Tweetnlp



(b) Compare model performance based on BERTweet



(c) Compare model performance in without sentiment case

Figure 4: Compare model performance in both scenarios

In addition, the results show that including SA may not significantly improve model performance at short periods ranging from 2 hours to 12 hours across all models tested. However, it appears to become a significant factor for longer periods (16 hours and beyond). Among the models evaluated, the GRU model with Tweetnlp sentiment achieved the highest accuracy score of 90.3%, F1-score of 90.3%, precision score of 91.41% and recall score of 91.18% at 16-hour lag. This was followed closely by the GRU model with Bertweet with an accuracy score of 90.2% and the same value of other metrics at 91.14%. The BiLSTM with Tweetnlp sentiment also produced impressive results, achieving an accuracy score of 89.44%, and F1, precision, and recall of 90.64%, 90.98%, and 90.3% respectively. While the overall performance of the LSTM model is lower than other models, it still exhibits an upward trend, particularly in the SA case. However, the LSTM model without sentiment case suddenly dipped at 16 hours and 17 hours. Furthermore, we find that the accuracy difference between the two scenarios is relatively small, just below 2%. However, we can see a significant gap in accuracy value achieved by the GRU model from 13 hours to 16 hours, with above 2% - 3% compared to other models. Additionally, the accuracy difference between the two SA datasets remains around 1%.

Findings in summary: This study investigated the impact of Twitter sentiment on DL models for Bitcoin price change prediction. We aimed to identify the optimal time lags for sentiment data to influence accuracy. In this section, we summarize our findings based on the following research questions. Based on our empirical results, the sentiment expressed in Tweets can significantly impact the Bitcoin price change depending on the specific time horizon. The experiment was divided into three different datasets for training and validation, including two with SA (Tweetnlp and Bertweet), and one without. All datasets were modified based on lag time intervals ranging from 2 hours to 17 hours, meaning that each instance consists of all features within time period. The results show that the maximum accuracy of each model was achieved by incorporating SA. The highest accuracy of our paper is 90.3%, reached by a 2-layer GRU trained on a dataset with Tweetnlp sentiment at a 16-hour lag. However, SA might not be a significant factor within the first 12 hours. This explains why models without SA had better performance during this timeframe. GRU outperforms other prediction models LSTM and BiLSTM in both sentiment and non-sentiment scenarios. In the non-sentiment case, it achieved a maximum accuracy of 87.47% at a 17-hour lag. When SA was included, the GRU reached a maximum accuracy of 90.3% at a 16-hour lag. Following up, the BiLSTM also had competitive results with 87.47% at a 14-hour lag in without sentiment combination and 89.44% at a 17-hour lag in sentiment included. Furthermore, there is no significant difference between the two SA generated from Tweetnlp and Bertweet, which remains around 1%. During our time intervals being tested, the difference in both scenarios is quite small, falling in a range of 1% - 2% in most models. However, the GRU model exhibited a slightly bigger gap of around 2%-3% from 13 hours to 16 hours. Identifying the optimal lag time for the highest accuracy depends on both the model and whether SA is included. For incorporating SA, the highest accuracy is achieved at a 16-hour lag, while the best lag time for non-sentiment included is a 17-hour. Compared to our models, the best time lags are 16-hour for GRU and 17-hour for both BiLSTM and LSTM models. It's important to note that these results are based on a limited timeframe, and the optimal lag times may differ for longer datasets. In our limited time horizon for analysis, we can say the optimal lag time intervals are 16-hour and 17-hour.

5 CONCLUSION

In conclusion, this study has focused on predicting Bitcoin price movement and recognizing the dynamic nature of cryptocurrency markets. Through meticulous analysis of Twitter sentiment and deep learning models, we have identified optimal time lags and model architectures for enhancing prediction accuracy. While Bitcoin price movements may vary, our findings provide valuable insights into leveraging SA and temporal patterns to navigate the cryptocurrency landscape effectively.

REFERENCES

[1] Jose Camacho collados et al. 2022. TweetNLP: Cutting-Edge Natural Language Processing for Social Media. *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations* (2022). https://doi.org/10.18653/v1/2022.emnlp-demos.5

[2] A. Dimitriadou and A. Gregoriou. 2023. Predicting Bitcoin Prices Using Machine Learning. *Entropy* (2023). https://doi.org/10.3390/e25050777

[3] Frohmann et al. 2023. Predicting the Price of Bitcoin sing Sentiment-Enriched Time Series Forecasting. *Big Data Cogn. Comput* (2023). https://doi.org/10.3390/bdcc7030137

[4] Giulia Serafini et al. 2020. Sentiment-Driven Price Prediction of the Bitcoin based on Statistical and Deep Learning Approaches. *2020 International Joint Conference on Neural Networks (IJCNN)* (2020), 19–24. https://doi.org/10.1109/IJCNN48605.2020.9206704

[5] Ibrahim et al. 2021. Predicting market movement direction for bitcoin: A comparison of time series modeling methods. *Engineering* (2021). https://doi.org/10.1016/j.compeleceng.2020.106905

[6] Ifigeneia Georgoula et al. 2015. Using Time-Series and Sentiment Analysis to Detect the Determinants of Bitcoin Prices. (2015). https://doi.org/10.2139/ssrn.2607167

[7] Jeffrey Chu et al. 2017. GARCH Modelling of Cryptocurrencies. *Journal of Risk and Financial Management* 10, 4 (2017), 17. https://doi.org/10.3390/jrfm10040017

[8] J.M. Low et al. 2023. Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction. In *Advances in Visual Informatics: IVIC 2023 (Lecture Notes in Computer Science, Vol. 14322)*. Springer, Singapore. https://doi.org/10.1007/978-981-99-7339-2_4

[9] Juan Manuel Pérez et al. 2021. pysentimiento: A Python Toolkit for Opinion Mining and Social NLP tasks. *Computation and Language* (2021). https://doi.org/10.48550/arXiv.2106.09462

[10] Kate Murray et al. 2023. On Forecasting Cryptocurrency Prices: A Comparison of Machine Learning, Deep Learning, and Ensembles. *Forecasting* 5, 1 (2023), 196–209. https://doi.org/10.3390/forecast5010010

[11] Markus Frohmann et al. 2023. Predicting the Price of Bitcoin Using Sentiment-Enriched Time Series Forecasting. *Big Data Cogn. Comput* 7, 3 (2023), 14–15. https://doi.org/10.1109/MACS48846.2019.9024772

[12] P. Basile et al. 2017. *Sentiment Analysis of Microblogging Data*. Springer, New York, NY. https://doi.org/10.1007/978-1-4614-7163-9_110168-1

[13] Sudhanshu Kumar et al. 2023. A Comprehensive Review on Sentiment Analysis: Tasks, Approaches and Applications. *arXiv* (2023). https://doi.org/10.48550/arXiv.2311.11250

[14] Wang Zhengyang et al. 2019. Prediction of Cryptocurrency Price Dynamics with Multiple Machine Learning Techniques. *ICMLT '19: Proceedings of the 2019 4th International Conference on Machine Learning Technologies* (2019), 15–19. https://doi.org/10.1145/3340997.3341008

[15] Zeba Ayaz et al. 2020. Bitcoin Price Prediction using ARIMA Model. *TechRxiv* (2020). https://doi.org/10.36227/techrxiv.12098067.v1

[16] Zhenyu Liu et al. 2020. Forecast Methods for Time Series Data: A Survey. *IEEE Access* (2020). https://doi.org/10.1109/ACCESS.2021.3091162

[17] Jacques Vella Critien; Albert Gatt and Joshua Ellul. 2022. Bitcoin price change and trend prediction through twitter sentiment and data volume. *Financ Innov 8, 45* (2022). https://doi.org/10.1186/s40854-022-00352-7

[18] S. Bhatt; M. Ghazanfar and M. Amirhosseini. 2023. Sentiment-Driven Cryptocurrency Price Prediction: A Machine Learning Approach Utilizing Historical Data and Social Media Sentiment Analysis. *Machine Learning and Applications: An International Journal (MLAIJ)* 10, 2/3 (2023), 1–15. https://doi.org/10.5121/mlaij.2023.10301

[19] Yiqing Hua. 2020. Bitcoin price prediction using ARIMA and LSTM. In *2020 International Symposium on Energy, Environmental Science and Engineering (ISEESE 2020)*. https://doi.org/10.1051/e3sconf/202021801050

[20] C. Hutto and Eric Gilbert. 2014. VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *(2014): Eighth International AAAI Conference on Weblogs and Social Media* 8, 1 (2014), 14–15. https://doi.org/10.1609/icwsm.v8i1.14550

[21] Rob J. Hyndman and George Athanasopoulos. 2021. *Forecasting: principles and practice* (3rd ed.). OTexts, Melbourne, Australia. https://otexts.com/fpp3/

[22] Patrick Jaquart; Sven Köpke and Christof Weinhardt. 2022. Machine learning for cryptocurrency market prediction and trading. *The Journal of Finance and Data Science* 8 (November 2022), 331–352. https://doi.org/10.1016/j.jfds.2022.12.001

[23] Kristoufek L. 2015. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLoS ONE 10(4): e0123923s* (2015). https://doi.org/10.1371/journal.pone.012392

[24] Lingyun Zhao; Lin Li and Xinhao Zheng. [n. d.]. A BERT based Sentiment Analysis and Key Entity Detection Approach for Online Financial Texts. *Computation and Language* ([n. d.]), 2020. https://doi.org/10.48550/arXiv.2001.05326

[25] Md Shohel Sayeed; Varsha Mohan and Kalaiarasi Sonai Muthu Anbananthen. 2023. BERT: A Review of Applications in Sentiment Analysis. *HighTech and Innovation Journal* 4, 2 (2023), 453–462. https://doi.org/10.28991/HIJ-2023-04-02-015

[26] Muhammad Rizwan; Sanam Narejo and Moazzam Javed. 2019. Bitcoin price prediction using Deep Learning Algorithm. *2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)* (2019), 14–15. https://doi.org/10.1109/MACS48846.2019.9024772

[27] Nakamoto S. 2009. Bitcoin: A Peer-to-Peer Electronic Cash System. (2009). https://bitcoin.org/bitcoin.pdf

[28] Muhammad Sanwal and Muhammad Mamoon Mazhar. 2019. Performance Comparison of Machine Learning and Deep Learning Models for Sentiment Analysis of Hotel Reviews. *International Journal of Information Technology and Applied Sciences (IJITAS)* 5, 1 (2019), 01–07. https://doi.org/10.5281/zenodo.8225185

[29] Yang Si. 2022. Using ARIMA model to analyse and predict bitcoin price. *BCP Business and Management* 34 (2022), 1210–1216. https://doi.org/10.54691/bcpbm.v34i.3161

[30] Dat Quoc Nguyen; Thanh Vu and Anh Tuan Nguyen. 2020. BERTweet: A pre-trained language model for English Tweets. *In Proceedings of EMNLP 2020: System Demonstrations* (2020). https://doi.org/10.48550/arXiv.2005.10200