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Public Perception And Sentiment On Social Media X Towards The Interest In Adopting Bitcoin As A Digital Asset

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Abstract: This study analyzes the relationship between public sentiment on the social media platform X and Bitcoin's global price volatility from January to October 2024. Using sentiment analysis supported by the BERT machine learning model and the Support Vector Machine (SVM) algorithm, relevant tweets were classified into positive, neutral, and negative sentiments. Model evaluation demonstrated excellent performance, with precision, recall, and F1-score for positive sentiment reaching 95.52%, 93.57%, and 94.53%, respectively. Neutral sentiment achieved precision of 88.61%, recall of 92.11%, and an F1-score of 90.32%. Negative sentiment yielded precision of 92.02%, recall of 91.05%, and an F1-score of 91.53%. The results indicate a significant correlation between public sentiment and Bitcoin price movements, where positive sentiment drives price increases while negative sentiment often triggers sell-offs. Moreover, the intensity of social media discussions significantly impacts market dynamics, as evidenced by a spike in activity in March 2024 coinciding with Bitcoin's price peak during the study period. These findings provide insights for investors, market analysts, and regulators to understand the role of social media as a market sentiment indicator influencing digital asset volatility.

Keyword: Social Media X, Bitcoin, Sentiment Analysis, Price Volatility

INTRODUCTION

Bitcoin, as one of the most popular digital assets in the world, has been the focus of many parties, from individual investors to large financial institutions (Widyarani, Widiati, & Ujianti, 2022). Bitcoin's highly volatile price movements are not only influenced by traditional factors such as demand and supply, but also by the growing public sentiment on social media (Liu, 2022). Platforms like X (formerly Twitter) serve as the premier venue for discussion, opinions, and news related *to cryptocurrencies*. The sentiment that emerges on social media often plays a crucial role in shaping market expectations, thus influencing investment decisions and Bitcoin price movements (Bollen, Mao, & Zeng, 2011).

Research by Sofiati (2021) suggests that the perceived quality of a product, such as Bitcoin's security features and potential for significant returns, can drive consumer interest and adoption. This aligns with the growing trend of younger generations, like Generation Z, who are more open to adopting new technologies such as Bitcoin (Ali, 2020). On the other hand, older generations tend to be more skeptical, preferring traditional investment methods. These generational differences influence Bitcoin adoption rates across various age groups.

Bitcoin's extreme price volatility can be seen from its price fluctuations, such as in 2024, when the price of Bitcoin moved from around $23,000 in January to $35,000 in October (Chan-Lau & Quach, 2023). These price spikes often occur in conjunction with an increase in the volume of conversations on social media. For example, in March 2024, the volume of conversations about Bitcoin on X increased to 100,000 *tweets*, followed by a price increase of up to $30,000. This phenomenon shows a relationship between the intensity of public conversations and Bitcoin price movements. Another study also noted that positive sentiment on social media often drives price increases, while negative sentiment tends to trigger a sell-off (Liew, 2016).

The role of social media in investment decision-making is increasingly significant. Based on a survey conducted by Statista in 2023, around 40% of individual investors use social media as their primary source of investment information (Li & Beck, 2021). Platforms like X allow for the dissemination of news, discussions about prices, as well as the formation of public opinion that can create "*hype*" or fear (*fear, uncertainty, doubt/FUD*). For example, a *tweet* from a well-known figure in the tech industry in January 2024 led to a spike in discussions about Bitcoin on X, which was followed by a 10% price increase within 24 hours (Liputan6, 2024). In addition, analytical data from X shows that conversations about Bitcoin increased by 30% in the first half of 2024 compared to the previous year, which reinforces the relevance of the study (TwitterAnalytics, 2024).

As noted by Rahmi (2020), both external factors (e.g., government policies) and internal factors (e.g., technological advancements) influence Bitcoin's price. Policies supporting or restricting Bitcoin can either increase or decrease public trust, while technological improvements can enhance security and efficiency, further legitimizing Bitcoin as an investment option. Sakti (2016) highlights the importance of marketing elements, such as price, in influencing public perception. Fluctuations in Bitcoin's price, driven by social media sentiment, play a key role in shaping how people view its value.

Sajekti (2017) further emphasizes that fluctuations in Bitcoin’s price, much like commodities, can be influenced by external factors such as economic conditions and market sentiment, with social media playing a vital role in these dynamics. The public’s perception of Bitcoin’s value is often shaped by media discussions, which can either drive demand or cause panic selling, highlighting the importance of understanding these external factors.

The urgency of this research lies in the lack of studies that integrate *real-time social media sentiment data* with real-time analysis of Bitcoin price movements. (Bollen et al., 2011). A better understanding of the relationship between social media sentiment and Bitcoin's price volatility can assist investors in making more rational and informative decisions. In addition, the study is also relevant for regulators and policymakers who want to understand the impact of social media on financial markets. With the aim of identifying patterns of relationships between social media sentiment on X and Bitcoin price movements globally, this study is expected to provide new insights into the role of social media in influencing the digital asset market and provide data-driven guidance for the crypto community and market participants (Liu, 2022).

The purpose of this study is to analyze the relationship between public sentiment on social media X (formerly Twitter) and Bitcoin price movements globally in the period January to October 2024. This study aims to identify the relationship pattern between positive, neutral, and negative sentiment and Bitcoin price volatility, as well as evaluate the extent to which the intensity of conversation volume on social media affects the price fluctuations of this digital asset.

By understanding the correlation between social media sentiment and Bitcoin price movements, this research is expected to provide useful insights for investors (Fegiyanto, Hermawan, & Ardiani, 2024), market analysts, and the crypto community to make more rational decisions. In addition, the results of this study are also expected to be a reference for regulators in managing the impact of social media on the stability of the digital asset market.

METHOD

This study will use a quantitative approach with secondary data analysis. The research process includes several key stages, from data collection to analysis of results. The research will combine text mining methods, sentiment analysis, and statistical analysis to evaluate the relationship between social media sentiment X and Bitcoin price movements. This type of research is descriptive correlational, with the aim of identifying the pattern of relationships between public sentiment on social media X (Twitter) and Bitcoin price volatility.
The stages of this research method are, Data Scraping Collection (Metsos X), Data Preprocessing, Tokenization, Sentiment Analysis (BERT Model, Sentiment Distribution, Evaluation and Visualization).

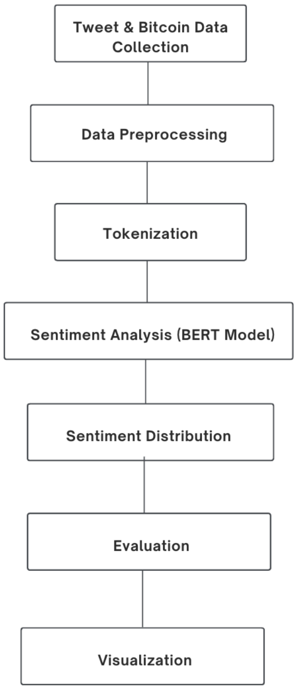

Figure 1. Research Outline

Variable Operationalization

The variables that will be used in this study consist of Independent Variables and Dependent Variables, the explanation is as follows :

1. Independent Variable
   Social media sentiment (positive, neutral, negative) as measured by the text of the tweet.
2. Dependent Variable
   Bitcoin price movement, which is measured from the daily opening and closing prices.

Data Collection Techniques

Tweet Data Collection on X

The data is obtained through X's official API (formerly Twitter), which is used to download tweets based on specific keywords such as "Bitcoin" and "BTC." Data collection is limited to the research period, which is from January to October 2024, to ensure relevance to the research objectives. The data of 760,000 tweets collected is then stored in CSV format to facilitate further analysis in a structured and systematic manner.

Table 1 Tweet Data from Social Media Scraping X

No	Tweet	ID Account X	Time	Reply	Repost	Like	View
1	🇺🇸TRUMP: "Never sell your Bitcoin." When the President says don't sell your #Bitcoin, you listen.	@Cointelegraph	12:00 AM . Oct 11, 2024	313	2.4K	12K	723K
2	90K and going… Another ATH for #Bitcoin!	@binance	09:31 PM . Oct 13 2024	1.3K	1K	4.6k	344.3K
3	#BITCOIN MOONVEMBER IS SO REAL!🚀	@rovercrc	03.02 PM . Oct 12, 2024	260	273	1.4K	98K
4	BREAKING: $93,500 #Bitcoin 🇺🇸🎉 — $BTC ATH	@Swan	1:18 AM · Oct 20, 2024	24	83	551	17.5 K
5	Michael Saylor says #Bitcoin is going to $13 million on CNBC 👀	@saylordocs	1:00 AM · Oct 14, 2024	200	1.2K	9.8K	1M
6	🔥 KEVIN O'LEARY: "#Bitcoin is gonna hit $100,000 long before the holiday I think."	@Cointelegraph	3:00 PM · Oct 20, 2024	40	76	326	17.9K

Bitcoin Price Data Collection on CoinMarketCap

Bitcoin price data is obtained from the trusted platform CoinMarketCap, which provides real-time as well as historical cryptocurrency price information. Data collection is carried out through CoinMarketCap's official API to access Bitcoin daily price information, including the opening price, closing price, and high and low prices. The data collected is limited to the relevant period, namely from January to October 2024 or as many as 304 days. The entire data is then saved in a tabular format (CSV or Excel) for easy further analysis using statistical tools.

Table 2 CoinMarketCap Bitcoin Price Data

No	Timeopen	Open	High	Low	Close
1	2024-10-01 T00:00:00.000Z	63335.603583719	73577.2096582116	58895.2078078197	70215.1856325839
2	2024-09-01 T00:00:00.000Z	58969.7994536059	66480.6947101072	52598.6996623841	63329.4981294766
3	2024-08-01 T00:00:00.000Z	64625.8404447144	65593.244771184	49121.2373775943	58969.8983660431
4	2024-07-01 T00:00:00.000Z	62673.6063386528	69987.5422080099	53717.3754334207	64619.2496492185
5	2024-06-01 T00:00:00.000Z	67489.6117770498	71907.8489829092	58601.7000722967	62678.292079457
6	2024-05-01 T00:00:00.000Z	60609.4979456889	71946.462688481	56555.2940546252	67491.4170108375
7	2024-04-01 T00:00:00.000Z	71333.4847168797	72715.3596085505	59120.0680465683	60636.8567800147
8	2024-03-01 T00:00:00.000Z	61168.0624293716	73750.07385038	59323.9089421326	71333.6479258644
9	2024-02-01 T00:00:00.000Z	42569.7613984399	63913.1318135774	41879.1899911815	61198.382897303

The average price of Bitcoin in the period January to October 2024 is calculated based on the exchange rate in USD and IDR, with the aim of providing a comprehensive overview of Bitcoin's price fluctuations during that time period.

Table 3 Average Bitcoin Price in the Period January – October 2024

No	Moon	Bitcoin Price Average (USD)	Bitcoin Price Average (IDR)
1	January	$42919.61224420088	Rp 683,742,498
2	February	$49875.17443398331	Rp 794,549,964
3	March	$67702.43881180164	Rp 1,078,552,024
4	April	$65882.37971545855	Rp 1,049,557,080
5	May	$65266.31702151933	Rp 1,039,742,727
6	June	$65899.4657878101	Rp 1,049,772,487
7	July	$62804.54195749874	Rp 1,000,470,632
8	August	$59921.19742474016	Rp 954,539,216
9	September	$60358.51550682287	Rp 961,505,654
10	October	$65422.66711027435	Rp 1,042,177,127

Preprocessing Data

Data preprocessing is an important stage in the analysis of raw data from X to ensure the quality and relevance of the data before further analysis (Rahayu et al., 2024). Raw data downloaded from X often contains irrelevant elements, such as URLs, emojis, punctuation, custom symbols, and numbers, which have no contribution to sentiment analysis. Therefore, the first step in preprocessing is to clean up the text by removing those elements, including hashtags and user mentions, which are less likely to provide meaningful sentiment information. This process also includes normalizing the text, such as converting uppercase to lowercase letters to ensure consistency in analysis.

The next stage is the removal of stopwords, which are common words that have no sentimental value, such as "and," "or," "with," or "the." Stopwords are removed because their existence only adds to the complexity of the data without providing important information for analysis. After cleaning, the text can be further processed through stemming or lemmatization, i.e. changing the word to its basic form to ensure more accurate sentiment analysis. The result of this preprocessing is clean, structured, and ready-to-use text data in sentiment analysis using the Natural Language Processing (NLP) method.

Table 4 Preprocessing Data

No	Tweet Data Preprocessing Results
1	*trump never sell bitcoin president says dont sell listen*
2	*k going another ath*
3	*moonvember real*
4	*breaking btc ath*
5	*michael saylor says going million cnbc*
6	*kevin oleary gon na hit long holiday think*

Tweet Data Tokenization

Tokenization is the process of breaking down text into small units called tokens, such as words, phrases, or even individual characters, depending on the needs of the analysis. In sentiment analysis or Natural Language Processing (NLP), tokenization serves as the first step to understanding the structure of the text and separating the raw text into elements that can be analyzed separately. For example, the sentence "Bitcoin price rises dramatically" will be broken down into tokens ["Price," "Bitcoin," "up," "drastically"]. This process helps in identifying relevant keywords for further analysis, such as positive, negative, or neutral sentiment in a text.

The tokenization process can also be adjusted to the needs of analysis, such as tokenization based on words (word tokenization) or sentences (sentence tokenization). In some cases, tokenization is done in conjunction with data cleansing, such as removing irrelevant punctuation marks or symbols. The resulting tokens form the basis for the next steps, such as normalization, removal of stopwords, and sentiment analysis. With tokenization, text that was initially unstructured can be transformed into a more organized form, making it easier to process using NLP algorithms or machine learning techniques.

Table 5 Tweet Data Tokenization

No	Tweet Data Preprocessing Results	Word Tokens
1	*trump never sell bitcoin president says dont sell listen*	'trump', 'never', 'sell', 'bitcoin', 'president', 'says', 'dont', 'sell', 'listen'
2	*k going another ath*	'k', 'going', 'another', 'ath'
3	*moonvember real*	'moonvember', 'real'
4	*breaking btc ath*	'breaking', 'btc', 'ath'
5	*michael saylor says going million cnbc*	'michael', 'saylor', 'says', 'going', 'million', 'cnbc'
6	*kevin oleary gon na hit long holiday think*	‘kevin', 'oleary', 'gon', 'na', 'hit', 'long', 'holiday', 'think'

Sentiment Analysis

Machine learning-based approaches are used in sentiment analysis to improve accuracy and capture the nuances of complex sentiment in text. One of the models used is BERT (Bidirectional Encoder Representations from Transformers), a transformer-based model that excels in understanding word contexts in a two-way way. Unlike traditional approaches, BERT is able to understand the meaning of words based on the relationships between words in the entire text, not just the local context. In this study, BERT was used to process texts from social media and classify sentiments into positive, neutral, or negative. The model is trained using a manually annotated dataset, so it can learn relevant sentiment patterns in Bitcoin-related tweet data.

The sentiment classification algorithm uses the Support Vector Machine (SVM). Sentiment classification is carried out based on the polarity score generated by the model. If the polarity value is greater than zero (polarity>0), the sentiment is considered positive. Conversely, if the polarity value is equal to zero (polarity=0), sentiment is classified as neutral, while a polarity value less than zero (polarity<0) indicates negative sentiment. This approach allows for more precise analysis than rule-based methods, as the BERT model can understand more complex sentence contexts, such as sarcasm or the use of slang. Thus, this approach provides more accurate results for analyzing the relationship between social media sentiment and Bitcoin price movements.

Table 6 Sentiment Analysis

No	Tweet Before Preprocessing	Tweet After Preprocessing	Polarity Value	Sentiment Analysis
1	🇺🇸TRUMP: “Never sell your Bitcoin.” When the President says don’t sell your #Bitcoin, you listen.	trump never sell bitcoin president says dont sell listen	0.0	Neutral
2	90K and going… Another ATH for #Bitcoin!	k going another ath	0.0	Neutral
3	#BITCOIN MOONVEMBER IS SO REAL!🚀	moonvember real	0.2	Positive

No	Tweet Before Preprocessing	Tweet After Preprocessing	Polarity Value	Sentiment Analysis
4	BREAKING: $93,500 #Bitcoin 🇺🇸🎉 — $BTC ATH	breaking btc ath	0.0	Neutral
5	Michael Saylor says #Bitcoin is going to $13 million on CNBC 👀	michael saylor says going million cnbc	0.0	Neutral
6	🔥 KEVIN O'LEARY: "#Bitcoin is gonna hit $100,000 long before the holiday I think."	kevin oleary gon na hit long holiday think	-0.05	Negative

Sentiment Distribution

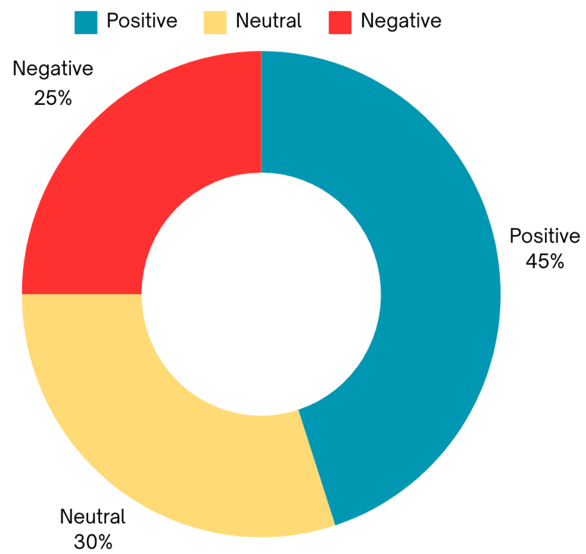

Figure 2 Distribution of Sentiment on Bitcoin Quotes

The distribution of sentiment regarding Bitcoin mentions from January to October 2024 shows that the majority of sentiment is positive, which accounts for 45% (342,000 Tweets) of the total discussions. This reflects the high optimism from the social media user community towards Bitcoin during the period, which may have been driven by Bitcoin's price rise and positive developments in the cryptocurrency industry. This positive sentiment is likely related to good news, such as the adoption of blockchain technology by major institutions, supportive regulations, or bullish market trends.

On the other hand, about 30% (228,000 Tweets) of discussions have neutral sentiment, which indicates that most users only share information or discussions without any specific expression of emotion. Meanwhile, negative sentiment was recorded at 25% (190,000 Tweets), reflecting concern or dissatisfaction with price fluctuations or other issues, such as strict regulation or potential market manipulation. This distribution illustrates how public opinion on social media has a diverse viewpoint towards Bitcoin, which can affect market expectations and price movements.

RESULTS AND DISCUSSION

Total Tweet Period January – October 2024

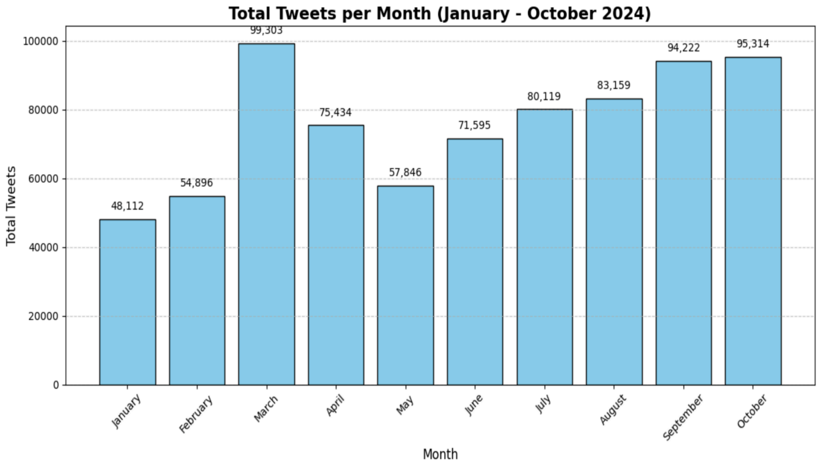

Figure 3 Total Number of Tweets for the Period Jan – Oct 2024

The graph above illustrates the total number of tweets discussing Bitcoin each month during the period January to October 2024. The data shows a significant increase in Bitcoin-related social media activity, with the peak number of tweets recorded in March, reaching 99,303 tweets. The lowest activity occurred in January, with a total of 48,112 tweets. After a decline in May, the number of tweets increased gradually again until October, when it recorded 95,314 tweets. The spike in tweets in a given month is most likely influenced by major events or news in the cryptocurrency market, reflecting the intense attention and discussion on social media towards Bitcoin during the period. This pattern highlights the relationship between social media activity and the level of public interest in Bitcoin.

Positive Sentiment Tweet Words

Figure 4 Positive Sentiment Tweet Words

The image above is an image depicting the words that most often appear in tweets with positive sentiment related to Bitcoin. Words like "Bitcoin," "bullish," "market," "major," and "reaches" dominate, reflecting high optimism among social media users toward Bitcoin. Terms such as "crypto," "investors," and "boom" also indicate expectations for significant growth in the cryptocurrency market. The presence of these words indicates that conversations with positive sentiment often focus on price increases, market stability, and investment opportunities. These visualizations provide important insights into topics and emotions that drive positive sentiment in the crypto community on social media.

Neutral Sentiment Tweet Words

Figure 5 Neutral Sentiment Tweet Words

The image above is an image depicting the words that most often appear in tweets with neutral sentiment regarding Bitcoin. Words such as "Bitcoin," "currently," "trading," and "market" dominate, reflecting that neutral tweets mostly contain information or updates regarding market conditions without indicating any particular opinion or emotion. Terms such as "price," "steady," "holds," and "update" indicate that these discussions tend to be descriptive and focus on the current status of Bitcoin, such as price movements or trading trends. This word cloud provides insight that neutral sentiment is often used to convey market information objectively without the influence of positive or negative opinions.

Neutral Sentiment Tweet Words

Figure 6 Neutral Sentiment Tweet Words

The image above shows the words that most often appear in tweets with negative sentiment related to Bitcoin. Words like "Bitcoin," "market," "plunges," and "crash" dominate, reflecting social media users' concerns about a sharp drop in Bitcoin's price or unstable market conditions. Other terms such as "fears," "falls," "drops," and "worried" highlight the anxiety and uncertainty felt by investors. These words often appear in the context of news or events that trigger fear, such as strict regulation, high volatility, or a major drop in the cryptocurrency market. This visualization provides important insights into the factors that trigger negative sentiment in the crypto community and their impact on market perception.

Bitcoin Price Comparison and Tweet Sentiment on X

Table 7 Bitcoin Price Comparison and Tweet Sentiment on X

No	Month	Average Bitcoin Price (USD)	Average Bitcoin Price (IDR)	Total Tweets	Sentimen Tweet		
					Positive	Neutral	Negative
1	January	$42919.61224420088	*Rp 683,742,498*	48.112	22.275	14.850	12.375
2	February	$49875.17443398331	*Rp 794,549,964*	54.896	24.344	16.228	13.524
3	March	$67702.43881180164	*Rp 1,078,552,024*	99.303	42.311	28.206	23.505
4	April	$65882.37971545855	*Rp 1,049,557,080*	75.434	33.946	22.630	18.858
5	May	$65266.31702151933	*Rp 1,039,742,727*	57.846	25.807	17.203	14.336
6	June	$65899.4657878101	*Rp 1,049,772,487*	71.595	32.259	21.505	17.921
7	July	$62804.54195749874	*Rp 1,000,470,632*	80.119	36.055	24.035	20.029
8	August	$59921.19742474016	*Rp 954,539,216*	83.159	40.194	26.796	22.330
9	September	$60358.51550682287	*Rp 961,505,654*	94.222	42.311	28.206	23.505
10	October	$65422.66711027435	*Rp 1,042,177,127*	95.314	44.331	29.553	24.628

The table above shows a comparison of the average Bitcoin price in USD and IDR with the number and distribution of tweet sentiment per month from January to October 2024. In general, there have been fluctuations in the price of Bitcoin throughout the period, with the highest average price peak recorded in March ($67,702 or Rp 1,078,552,024) which also has the most total tweets at 99,303. The distribution of tweet sentiment shows that positive sentiment dominates every month, as in October, where 44,331 tweets (about 46.5% of the total) reflected optimism towards Bitcoin. Neutral and negative sentiment tends to be lower, but remains significant in describing concerns or stable market information. This table indicates a correlation between Bitcoin price fluctuations and activity and sentiment on social media, with spikes in tweets often occurring in tandem with significant changes in the price of Bitcoin.

Social Media Activity vs Bitcoin Price

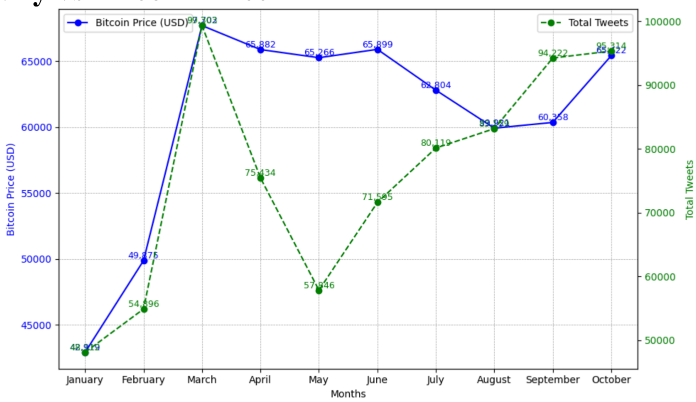

Figure 7 Social Media Activity vs Bitcoin Price Period Jan – Oct 2024

The image above shows the relationship between social media activity, measured through the total number of Bitcoin-related tweets, and the average price of Bitcoin in USD from January to October 2024. Chart patterns show similar fluctuations, where spikes in social media activity often occur in conjunction with significant changes in the price of Bitcoin. The peak in the number of tweets was recorded in March with over 99,000 tweets, which coincided with Bitcoin's rise in price to the highest level during this period, which was $67,702. This shows that discussions on social media increase substantially when there is a price momentum or a major event related to Bitcoin.

On the other hand, the number of tweets declined during April to June, in tandem with the decline in Bitcoin's price which hit a low of $57,346 in May. However, from July to October, the number of tweets increased again, reflecting the growing public interest in Bitcoin, which was also accompanied by a price recovery. This pattern suggests a potential close relationship between social media activity and Bitcoin price dynamics, where conversation volume can serve as an early indicator of market sentiment and cryptocurrency price movements. These findings underscore the important role of social media as a key platform that influences market perception and investment decisions regarding Bitcoin.

Evaluation

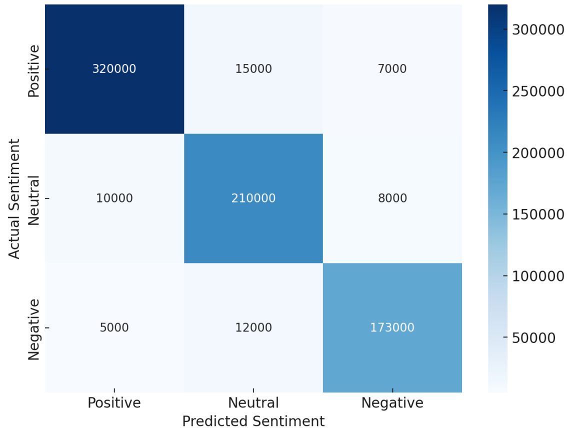

Figure 8 Heatmap Confusion Matrix

Based on the results of the model evaluation using the confusion matrix, the model shows excellent performance in classifying positive, neutral, and negative sentiments. For positive sentiment, the model managed to correctly predict as many as 320,000 data (True Positives) with a precision value of 95.52%, which shows that most of the positive sentiment predictions are correct. The recall of 93.57% reflects the model's ability to recognize actual data with positive sentiment. Overall, an F1-Score of 94.53% indicates an excellent balance between precision and recall in this category.

At neutral sentiment, the model correctly predicted as many as 210,000 data, resulting in an accuracy of 88.61%, indicating the prediction accuracy for this category. The recall reached 92.11%, indicating that the model was able to recognize most of the actual data with neutral sentiment. An F1-Score of 90.32% shows that the model has a stable and reliable performance in predicting this category.

Meanwhile, for negative sentiment, the model was able to correctly classify 173,000 data. A precision of 92.02% indicates that most predictions as negative sentiment are correct, while a recall of 91.05% indicates the model's ability to detect actual data with negative sentiment. An F1-Score score of 91.53% indicates a strong and consistent performance in this category.

Overall, the model has consistent performance with precision, recall, and F1-Score values above 90% for all sentiment categories. This shows that the model has a reliable ability to classify sentiment, with minimal classification errors. These results provide confidence that the model can be used effectively in real-world applications, such as social media sentiment analysis or other texts. Further improvements can be made by training the model on a more diverse dataset or using advanced optimization techniques to reduce classification errors between categories, particularly between neutral and negative sentiment.

CONCLUSION

This study shows a significant relationship between public sentiment on social media X (formerly Twitter) and Bitcoin price movements globally. The positive sentiment that dominates public discussions often goes hand in hand with the rise in the price of Bitcoin, reflecting the market's optimism towards this cryptocurrency. Conversely, negative sentiment reflected in discussions related to price declines or market volatility is often associated with Bitcoin price declines. This pattern was evident in the spike in discussions in March 2024, which coincided with the price of Bitcoin peaking during the research period. These results indicate that social media plays an important role as an indicator of market sentiment that influences expectations and investment decisions towards Bitcoin. The results of the analysis show that positive, neutral, and negative sentiment have a significant influence on Bitcoin price volatility. The dominating positive sentiment (45%) shows a major contribution to the rise in the price of Bitcoin, while the negative sentiment (25%) tends to trigger a sell-off and sharp price fluctuations. Neutral sentiment (30%) indicates that most discussions on social media are descriptive and do not directly affect price movements, but still provide context for overall market perception. In addition, the intensity of conversation volume on social media also has a significant impact on Bitcoin price fluctuations. The increase in tweet volume, as occurred in March 2024 with a total of 99,303 tweets, coincided with high price volatility, suggesting that discussion volume could be an early indicator of market movements. Overall, the study concludes that public sentiment and discussion activity on social media X play a significant role in influencing Bitcoin's price volatility. These findings provide useful insights for investors, market analysts, and regulators to understand the dynamics between social media and digital asset market movements. The application of sentiment analysis-based models can help identify market trends and support more rational investment decision-making.

REFERENCES

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8.

Sofiati, N. A. (2021). Analisis Produk, Harga, Promosi, Dan Tempat Terhadap Minat Beli Pada Factory Outlet PT Blossom Mandiri Sejati Cabang Dago.

Ali, M. M. (2020). Faktor Konsumen Dalam Memilih Tempat Belanja di Era 4.0. Jurnal Ilmu Manajemen dan Bisnis Islam, 37-44.

Chan-Lau, J. A., & Quach, L. (2023). Cryptocurrencies and Banking Sector Connectedness: Don't Worry, Be Happy… for Now. *Be Happy… for Now (December 1, 2023)*.

Fegiyanto, R., Hermawan, A., & Ardiani, F. (2024). Prediksi Harga Crypto dengan Algoritma Jaringan Saraf Tiruan. *Jurnal Indonesia: Manajemen Informatika Dan Komunikasi*, *5*(3), 2265–2275.

Li, A., & Beck, C. (2021). The Effects of Social Media Attention and Sentiment on Initial Public Offering Returns. *Journal of Student Research*, *10*(4).

Liew, J. K. (2016). Twitter Sentiment and Stock Prices: Evidence from the S&P 500. Twitter Sentiment and Stock Prices: Evidence from the S&P 500, (1–22).

Liputan6. (2024). Volume Percakapan Bitcoin Melonjak pada Maret 2024. Retrieved from Volume Percakapan Bitcoin Melonjak pada Maret 2024. Retrieved from https://www.liputan6.com

Liu, B. (2022). *Sentiment analysis and opinion mining*. Springer Nature.

Rahayu, P. W., Sudipa, I. G. I., Suryani, S., Surachman, A., Ridwan, A., Darmawiguna, I. G. M., … Maysanjaya, I. M. D. (2024). *Buku Ajar Data Mining*. PT. Sonpedia Publishing Indonesia.

TwitterAnalytics. (2024). Global Social Media Mentions on Bitcoin (January - October 2024). Retrieved from Global Social Media Mentions on Bitcoin (January - October 2024).

Rahmi, P. P. (2020). Analisis Daya Saing Dan Dampak Kebijakan Pemerintah Terhadap Komoditas Teh.

Sakti, A. R. (2016). Pengaruh Bauran Pemasaran Harga Terhadap Kepuasan Dan Dampaknya Terhadap Loyalitas Pelanggan.

Sajekti, T. &. (2017). Analisis harga komoditas dan harga pokok penjualan serta pengaruhnya terhadap laba kotor pada PT. Aneka Tambang (Persero) Tbk. Jurnal Indonesia Membangun, 1-15.

Widyarani, K. D. P., Widiati, I. A. P., & Ujianti, N. M. P. (2022). Kajian Yuridis Penggunaan Koin Kripto sebagai Alat Pembayaran di Indonesia. *Jurnal Preferensi Hukum*, *3*(2), 300–305.