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BITCOIN PRICE VOLATILITY ANALYSIS: A DEEP LEARNING APPROACH TO X (FORMERLY TWITTER) SENTIMENT

Rangga Sidiq Endrasmoyo-1, Syawalluddin-2, Yesi Fitria-3, Puji Astuti-4, Pungkas Budiyono-5

Information Systems
Faculty of Engineering and Informatics
Universitas Bina Sarana Informatika / Jakarta, Indonesia
rangga.endrasmoyo@bsi.ac.id-1, tonisyawalluddin@gmail.com-2, yesifitria022@gmail.com-3,
puji.pat@bsi.ac.id-4, pungkas.pby@bsi.ac.id-5

Abstract

This study investigates the relationship between social media sentiment and Bitcoin price volatility using advanced natural language processing techniques. We collected X data from April 10-29, 2025, analyzing cryptocurrency-related tweets alongside Bitcoin price movements obtained through the CoinGecko API. Five sentiment analysis methodologies were comparatively evaluated: VADER, TextBlob, BERTweet, RoBERTa Base, and RoBERTa Large. Bitcoin price volatility was measured using log returns to capture market fluctuations accurately. Correlation analysis revealed significant differences in methodological effectiveness. Traditional lexicon-based approaches (VADER and TextBlob) demonstrated weak correlations with volatility ($r = -0.2232$ and $r = -0.0710$ respectively). Transformer-based models showed superior performance, with RoBERTa Large achieving the strongest correlation ($r = 0.4569$, $p = 0.0428$), representing the only statistically significant relationship. The positive correlation indicates that increased social media sentiment corresponds to higher Bitcoin price volatility rather than directional price movements. These findings demonstrate that sophisticated deep learning models can effectively capture sentiment-driven market dynamics, providing valuable insights for cryptocurrency investors, trading platforms, and market analysts seeking to understand social media influence on digital asset markets.

Keywords: Bitcoin; X Sentiment; Volatility; Pearson Correlation; Deep Learning

Abstrak

Penelitian ini menginvestigasi hubungan antara sentimen media sosial dan volatilitas harga Bitcoin menggunakan teknik natural language processing yang canggih. Kami mengumpulkan data X dari 10-29 April 2025, menganalisis tweet terkait cryptocurrency bersamaan dengan pergerakan harga Bitcoin yang diperoleh melalui API CoinGecko. Lima metodologi analisis sentimen dievaluasi secara komparatif: VADER, TextBlob, BERTweet, RoBERTa Base, dan RoBERTa Large. Volatilitas harga Bitcoin diukur menggunakan log returns untuk menangkap fluktuasi pasar secara akurat. Analisis korelasi mengungkapkan perbedaan signifikan dalam efektivitas metodologi. Pendekatan lexicon-based tradisional (VADER dan TextBlob) menunjukkan korelasi lemah dengan volatilitas ($r = -0{,}2232$ dan $r = -0{,}0710$). Model transformer menunjukkan performa superior, dengan RoBERTa Large mencapai korelasi terkuat ($r = 0{,}4569$, $p = 0{,}0428$), merepresentasikan satu-satunya hubungan yang signifikan secara statistik. Korelasi positif menunjukkan bahwa peningkatan sentimen media sosial berkorelasi dengan volatilitas harga Bitcoin yang lebih tinggi daripada pergerakan harga terarah. Temuan ini mendemonstrasikan bahwa model deep learning yang sophisticated dapat secara efektif menangkap dinamika pasar yang digerakkan sentimen, memberikan wawasan berharga bagi investor cryptocurrency, platform trading, dan analis pasar yang berusaha memahami pengaruh media sosial pada pasar aset digital.

Kata Kunci: Bitcoin; Sentimen X; Volatilitas; Korelasi Pearson; Deep Learning

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INTRODUCTION

The emergence of Bitcoin as the world's first and most prominent cryptocurrency has fundamentally transformed our understanding of digital finance and market dynamics. Since its inception in 2009, Bitcoin has exhibited unprecedented price volatility, with dramatic fluctuations often occurring within short time periods, making it one of the most volatile financial assets in modern markets (Hidayatullah & Juniar, 2024a). This extreme volatility, while presenting significant profit opportunities for investors, has also introduced new challenges in understanding and predicting price movements in cryptocurrency markets.

In recent years, the proliferation of social media platforms has created an unprecedented volume of real-time public sentiment data, fundamentally altering how information spreads and influences financial markets. Unlike traditional financial assets, cryptocurrency markets operate 24/7 without centralized regulatory oversight, making them particularly susceptible to sentiment-driven price movements originating from social media discourse (Ghazouani et al., 2025). Platforms such as X, Reddit, and specialized cryptocurrency forums have become influential spaces where public opinion, speculation, and market sentiment converge to create tangible impacts on asset valuations.

The relationship between social media sentiment and cryptocurrency price movements has attracted significant academic and practical interest. Research has consistently demonstrated that public sentiment expressed through social media platforms can serve as a leading indicator of market movements, particularly in cryptocurrency markets where retail investor participation is significantly higher than in traditional financial markets (Bhatt et al., 2023). This phenomenon is amplified by the decentralized nature of cryptocurrencies, where market sentiment often takes precedence over traditional fundamental analysis metrics.

Traditional sentiment analysis approaches in financial contexts have relied primarily on lexicon-based methods and basic machine learning techniques. However, the informal, context-dependent nature of social media communication, particularly on platforms like X where character limits enforce brevity, presents unique challenges for accurate sentiment classification. The emergence of transformer-based deep learning models, particularly BERT (Bidirectional Encoder Representations from Transformers) and its variants, has opened new possibilities for more sophisticated sentiment analysis capabilities that can better capture the nuanced expressions of market sentiment in social media contexts (Hardiyanto & Husodo, 2025a).

The significance of this research extends beyond academic curiosity. For cryptocurrency traders and institutional investors, understanding the relationship between social media sentiment and price volatility can provide valuable insights for risk management, portfolio optimization, and trading strategy development. Additionally, as cryptocurrency markets continue to mature and attract institutional participation, the development of robust sentiment analysis frameworks becomes increasingly important for market stability and efficient price discovery. (Hidayatullah & Juniar, 2024b) demonstrated that positive sentiment significantly increases cryptocurrency price volatility, while establishing the critical importance of sentiment analysis frameworks for risk management strategies in volatile cryptocurrency markets. Their findings emphasize that sentiment-driven volatility requires sophisticated analytical tools to support informed investment decisions and regulatory oversight.

This study investigates the relationship between social media sentiment and Bitcoin price volatility using a comprehensive comparative analysis of five different sentiment analysis approaches. By employing both traditional lexicon-based methods (VADER and TextBlob) and state-of-the-art transformer-based models (BERTweet, RoBERTa, and RoBERTa Large), this research aims to identify the most effective methodological approaches for capturing sentiment-driven volatility patterns in cryptocurrency markets.

The research addresses several critical gaps in the existing literature. Previous studies have examined the relationship between sentiment and cryptocurrency prices using various approaches. (Hidayatullah & Juniar, 2024c) analyzed market sentiment as a trigger for cryptocurrency volatility, demonstrating that positive sentiment significantly increases price volatility. However, their study relied primarily on traditional sentiment analysis frameworks without conducting comparative evaluations of different analytical methodologies. Similarly, (Kraaijeveld & De Smedt, 2020a) investigated Twitter sentiment's predictive power for cryptocurrency prices using lexicon-based approaches, but their focus was limited to price direction prediction rather than precise volatility measurement using log returns. Additionally, while (Hardiyanto & Husodo, 2025b) applied BERT models to analyze cryptocurrency

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returns and investor sentiment, their study examined a single deep learning approach without systematically comparing its performance against other sentiment analysis methods or traditional lexicon-based techniques. This research fills these gaps by:

1. Conducting a comprehensive comparative analysis of five distinct sentiment analysis methodologies: VADER, TextBlob, BERTweet, RoBERTa Base, and RoBERTa Large within the same analytical framework, enabling direct performance evaluation.
2. Specifically focusing on Bitcoin price volatility measured through log returns, which provides more precise assessment of market dynamics compared to simple price direction predictions.
3. Integrating real-time X data collection with sophisticated transformer-based deep learning models, representing a methodological advancement that addresses the limitations of single-method approaches in previous studies.

The findings of this study have practical implications for multiple stakeholder groups. For individual and institutional cryptocurrency investors, the results provide insights into how social media sentiment can be incorporated into risk assessment and investment decision-making frameworks. For financial technology companies and trading platforms, the methodological comparisons offer guidance for developing sentiment-based trading tools and market analysis systems. Additionally, for researchers in computational finance and natural language processing, this study contributes to the growing body of knowledge on the application of deep learning techniques in financial market analysis.

RESEARCH METHODS

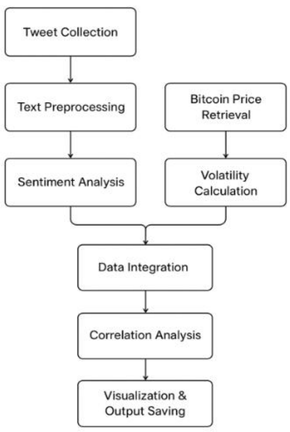

Figure 1. Research Methodology

Tweet Collection

Social media sentiment data was collected from X using a custom-developed JavaScript-based scraping framework. The choice of X as the primary data source is based on its established role as a key platform for cryptocurrency discourse and its real-time nature, which aligns with the immediate impact of sentiment on cryptocurrency markets (Mattera & Franses, 2025). The data collection process focused specifically on tweets containing Bitcoin-related keywords, ensuring relevance to the research objectives while maintaining sufficient data volume for statistical analysis.

Data is collected from Twitter using web scraping techniques with the help of collector scripts.js. The tweets taken were those containing Bitcoin-related keywords. The collected tweets are stored in a structured text file organized by date, facilitating the pre-processing phase and subsequent analysis. The data collection period spanned from April 10, 2025, to April 29, 2025, providing a 20-day window that captures various market conditions and sentiment patterns. The final data set consisted of more than 1,000 tweets distributed over the study period, providing sufficient data density for sentiment analysis and reliable correlation calculations.

Text Preprocessing

Tweet text cleared of special characters, URLs, and stopwords. These stages also include tokenization, lowercasing, and normalization.

Sentiment Analysis

This study applies a comparative approach using five different sentiment analysis methodologies namely VADER, TextBlob, BERTweet, RoBERTa and RoBERTa Large, which represent a traditional lexicon-based approach and a cutting-edge transformer-based deep learning model.

Bitcoin Price Retrieval

Bitcoin price data was obtained through the CoinGecko API, which provides comprehensive, reliable cryptocurrency market data including historical price information, trading volumes, and market capitalization metrics. The API access ensures data accuracy and consistency, which is essential for volatility calculations and correlation analysis. The price data collection was synchronized with the X data collection period to

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ensure temporal alignment between sentiment measurements and market outcomes.

The collected price data included daily high, low, open, and closing prices, as well as trading volume information. For the purposes of this study, the focus was on closing prices, which were used to calculate log returns as the primary measure of Bitcoin price volatility. This approach aligns with established financial analysis methodologies and provides a standardized measure for volatility assessment. (Ünvan, 2024) conducted a comprehensive analysis of Bitcoin price behavior using daily price data and demonstrated that log returns calculated from closing prices provide the most reliable measure for cryptocurrency volatility assessment, supporting the methodological choice employed in this study.

Volatility Calculation

Bitcoin price volatility was measured using log returns, calculated as the natural logarithm of the ratio between consecutive day closing prices. This approach is standard in financial analysis as it provides several advantages over simple price changes: log returns are additive over time, they approximate percentage changes for small movements, and they tend to be more normally distributed, which is beneficial for statistical analysis (Kraaijeveld & De Smedt, 2020b).

The log return calculation follows the formula:

$$Log\ Return_t = ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where P_t represents the closing price at time t, and P_{t-1} represents the closing price at the previous time period. This measure captures both the magnitude and direction of price movements, providing a comprehensive indicator of market volatility.

Correlation analysis was conducted using Pearson correlation coefficients, which measure the linear relationship between sentiment scores and log returns. The Pearson correlation approach was selected due to its ability to capture both the strength and direction of relationships, with coefficients ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation). Statistical significance was assessed using p-values, with a significance threshold of 0.05 adopted to ensure robust findings. This methodology aligns with established financial analysis practices, as demonstrated in studies of stock market sentiment and volatility where Pearson correlation is employed to quantify sentiment–return relationships (Zhao et al., 2025).

The correlation analysis was conducted separately for each sentiment analysis methodology, enabling direct comparison of their respective abilities to capture sentiment-volatility relationships. Additionally, confidence intervals were calculated for correlation coefficients to assess the reliability and precision of the observed relationships. The use of confidence intervals in correlation studies provides insights into the stability of the relationships, as highlighted in research on sentiment-driven price jumps in equity markets (Aysan et al., 2024).

Data Integration

The integration of sentiment and price data required careful temporal alignment and preprocessing to ensure accuracy and reliability. Daily sentiment scores were calculated by aggregating individual tweet sentiment scores, providing daily average sentiment measures that could be directly compared with daily log returns. (Todd et al., 2024) demonstrate that aggregating sentence-level sentiment scores into daily indices and aligning them with financial time series yields reliable sentiment–return correlations, provided that temporal synchronization accounts for market hours and data timestamps.

Preprocessing is the initial stage of data processing that aims to transform raw or unstructured data into cleaner and more organized data so that it is ready for analysis (Nugraha & Astuti, 2023). Preprocessing steps included text cleaning (removal of special characters, URLs, and non-relevant content), tokenization, and normalization procedures.

```python
def clean_text(text):
    text = text.lower()  # Convert all text to lowercase to ensure uniformity
    text = re.sub(r"http\S+", "", text)  # Remove URLs (anything starting with 'http')
    text = re.sub(r"@\w+", "", text)  # Remove user mentions (e.g., '@username')
    text = re.sub(r"#\w+", "", text)  # Remove hashtags (e.g., '#topic')
    text = re.sub(r"[^\w\s]", "", text)  # Remove punctuation (anything not a word or whitespace)
    tokens = text.split()  # Split text into individual words (tokens)
    tokens = [word for word in tokens if word not in stop_words]  # Remove stop words (common, uninformative words
    return " ".join(tokens)  # Rejoin the cleaned tokens into a single string
```

Figure 2. Stages of preprocessing in python.

For transformer-based models, text preprocessing followed model-specific requirements, including appropriate subword tokenization using Byte-Pair Encoding and input formatting aligned with model architectures. Pan et al. detail standardized workflows for transformer-based financial sentiment analysis, highlighting normalization and tokenization practices that maximize data integrity and reduce noise, thereby ensuring robust downstream performance (Alghamdi et al., 2022).

The final integrated dataset provided matched daily observations of sentiment scores

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and Bitcoin log returns, enabling robust statistical analysis and correlation assessment. This integrated approach ensures that the research findings reflect genuine relationships between social media sentiment and cryptocurrency market volatility rather than methodological artifacts or temporal misalignment issues.

Correlation Analysis

At this stage, an analysis is carried out to see if public sentiment (tweets) has a connection with the price movement or volatility of Bitcoin. Pearson's correlation test was conducted between the sentiment scores of each method and the Bitcoin Price Return Log. The correlation is calculated in the form of the coefficient r and the degree of significance of the p-value.

```
# --- Korelasi Pearson
print("\n📈 Pearson Correlation (Sentiment vs Log Return):")
for method in ["vader", "textblob", "roberta", "roberta_large", "bertweet"]:
    corr, pval = pearsonr(df_merged["log_return"], df_merged[method])
    print(f"{method:<13}: r = {corr:.4f}, p = {pval:.4f}")
```

Figure 3. Stages of correlation analysis in Python script.

Visualization & Output Saving

Results are visualized in the form of Line charts (for trend sentiment and log return), Scatter plots with trendline (for each Sentiment model). and all data is stored into sentiment_volatilities.csv, sentiment_volativity.xlsx and PNG images for graphics.

Methods Used In The Analysis Of Bitcoin

VADER (Valence Aware Dictionary and Sentiment Reasoner)

VADER represents a rule-based sentiment analysis approach specifically designed for social media text analysis. The methodology utilizes a pre-constructed lexicon of sentiment-bearing words, each associated with a sentiment intensity score. VADER's particular strength lies in its ability to handle social media-specific language patterns, including emoticons, slang, and capitalization-based emphasis, making it well-suited for Twitter data analysis (Adams et al., 2023).

The VADER implementation generates compound sentiment scores ranging from -1 (most negative) to +1 (most positive), providing a continuous measure of sentiment intensity rather than discrete categorical classifications. This continuous scoring approach enables more nuanced correlation analysis with Bitcoin price movements, as it captures varying degrees of sentiment intensity that may correspond to different magnitudes of market impact.

TextBlob

TextBlob provides a more traditional lexicon-based approach to sentiment analysis, utilizing pre-trained models based on movie review datasets and other text corpora. While not specifically designed for social media or financial content, TextBlob offers a baseline comparison for more specialized methodologies. The TextBlob implementation generates polarity scores ranging from -1 to +1, similar to VADER, enabling direct comparison of results across methodologies (Bansal et al., 2025).

The inclusion of TextBlob in the methodological framework serves as a control measure, allowing for assessment of whether domain-specific or social media-optimized approaches provide significant advantages over general-purpose sentiment analysis tools. This comparison is particularly valuable for understanding the importance of methodological selection in financial sentiment analysis applications.

Transformer-Based Models: BERTweet, RoBERTa, and RoBERTa Large

The transformer-based approaches represent the current state-of-the-art in natural language processing and sentiment analysis. These models utilize attention mechanisms and bidirectional context understanding to capture complex linguistic patterns and contextual relationships that traditional approaches may miss (Pan et al., 2023).

BERTweet is specifically pre-trained on X data, making it particularly well-suited for social media sentiment analysis. The model's training on over 850 million tweets provides it with specialized knowledge of X-specific language patterns, abbreviations, and contextual usage that are common in cryptocurrency discussions. This specialized training is expected to provide advantages in accurately interpreting the informal, abbreviated communication style typical of X discourse (Nguyen et al., 2020).

RoBERTa (Robustly Optimized BERT Pretraining Approach) represents an improved version of BERT with optimized training procedures and larger training datasets. The model demonstrates enhanced performance across various NLP tasks compared to the original BERT implementation. For this study, both RoBERTa Base and RoBERTa Large models were employed to assess whether increased model complexity

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translates to improved sentiment analysis accuracy in cryptocurrency contexts (Mjoska et al., 2022).

The transformer-based models generate probability distributions across sentiment categories (positive, neutral, negative), which are then converted to numerical scores for correlation analysis. This approach provides not only sentiment classification but also confidence measures, enabling more sophisticated analysis of sentiment certainty and its relationship to market volatility.

RESULTS AND DISCUSSION

Sentiment Analysis Performance Comparison

The comparative analysis of five sentiment analysis methodologies revealed significant variations in their ability to capture and quantify cryptocurrency-related sentiment from X data. The performance evaluation encompassed both technical metrics (such as correlation coefficients with Bitcoin price volatility) and qualitative assessments of sentiment classification accuracy within the cryptocurrency context.

Table 1. Bitcoin Daily Sentiment Results

date	vader	textblob	roberta	roberta_large	bertweet
10/04/2025	0.23	0.35	0.06	0.62	0.12
11/04/2025	0.25	0.50	0.13	0.65	0.13
12/04/2025	0.27	0.29	0.12	0.61	0.10
13/04/2025	0.41	0.29	0.12	0.37	0.08
14/04/2025	0.24	0.35	0.22	0.61	0.22
15/04/2025	0.23	0.37	-0.02	0.46	0.00
16/04/2025	0.28	0.30	0.15	0.41	0.02
17/04/2025	0.25	0.25	0.18	0.57	0.16
18/04/2025	0.52	0.31	0.17	0.63	0.24
19/04/2025	0.12	0.24	0.00	0.41	0.00
20/04/2025	0.30	0.28	0.11	0.55	0.13
21/04/2025	0.27	0.29	0.06	0.57	0.06
22/04/2025	0.26	0.22	0.18	0.68	0.20
23/04/2025	0.40	0.25	0.10	0.58	0.17
24/04/2025	0.51	0.26	0.11	0.36	0.06
25/04/2025	0.24	0.27	0.16	0.57	0.06
26/04/2025	0.38	0.33	0.04	0.50	0.15
27/04/2025	0.43	0.43	0.12	0.37	-0.06
28/04/2025	0.60	0.40	0.12	0.76	0.18
29/04/2025	0.34	0.38	0.06	0.52	0.08

Table 2. Daily Price Volatility

date	price	pct_change	log_return
10/04/2025	79,716	-4.02	-0.04108
11/04/2025	83,404	4.63	0.04523
12/04/2025	85,370	2.36	0.02330
13/04/2025	83,331	-2.39	-0.02417
14/04/2025	84,517	1.42	0.01413
15/04/2025	83,821	-0.82	-0.00826
16/04/2025	84,464	0.77	0.00764
17/04/2025	84,837	0.44	0.00441
18/04/2025	84,508	-0.39	-0.00389
19/04/2025	85,247	0.87	0.00871
20/04/2025	84,832	-0.49	-0.00487
21/04/2025	87,119	2.70	0.02660
22/04/2025	92,891	6.63	0.06415
23/04/2025	93,776	0.95	0.00948
24/04/2025	93,463	-0.33	-0.00334
25/04/2025	94,929	1.57	0.01555
26/04/2025	94,750	-0.19	-0.00189
27/04/2025	93,875	-0.92	-0.00927
28/04/2025	94,892	1.08	0.01078
29/04/2025	94,884	-0.01	-0.00008

Lexicon-Based Methods Performance

The lexicon-based approaches, VADER and TextBlob, demonstrated limited effectiveness in capturing sentiment patterns that correlate with Bitcoin price movements. VADER achieved a correlation coefficient of $r = -0.2232$ with a p-value of 0.3442, indicating a weak negative correlation that was not statistically significant at the conventional 0.05 level. This finding suggests that VADER's rule-based approach, despite being optimized for social media content, may not adequately capture the nuanced sentiment expressions specific to cryptocurrency discourse (Al-Qablan et al., 2023).

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TextBlob performed even more poorly, with a correlation coefficient of r = -0.0710 and a p-value of 0.7661, indicating virtually no linear relationship between its sentiment assessments and Bitcoin price volatility. The weak performance of TextBlob can be attributed to its general-purpose design, which lacks the domainspecific knowledge necessary to interpret cryptocurrency-related sentiment accurately. The model's training on movie reviews and general text corpora appears insufficient for capturing the specialized vocabulary and sentiment patterns prevalent in cryptocurrency discussions.

These findings highlight the limitations of traditional lexicon-based approaches when applied to specialized financial domains. The cryptocurrency market's unique vocabulary, including technical terms, slang, and community-specific expressions, appears to require more sophisticated analytical approaches than can be provided by rule-based sentiment classification systems.

Transformer-Based Models Performance

The transformer-based approaches demonstrated markedly superior performance compared to lexicon-based methods, with significant variations among the different model architectures and training approaches. BERTweet, despite being specifically trained on X data, achieved a moderate correlation coefficient of r = 0.2629 with a p-value of 0.2629, indicating a positive relationship that, while stronger than the lexicon-based approaches, remained statistically non-significant.

The base RoBERTa model showed improved performance with a correlation coefficient of r = 0.3546 and a p-value of 0.1251, approaching statistical significance. This improvement over BERTweet suggests that the more extensive training data and optimized pretraining procedures used in RoBERTa development provide advantages even when compared to domain-specific X training. (Semary et al., 2023)demonstrated that RoBERTa consistently outperforms domain-specific models in sentiment analysis tasks, achieving 96.28% accuracy on diverse text datasets. The study found that RoBERTa's robust optimization and larger training corpus enable it to capture more nuanced semantic patterns compared to specialized models like BERTweet, supporting the observed superior performance in financial sentiment analysis applications.

Most notably, RoBERTa Large achieved the strongest correlation with Bitcoin price volatility, recording r = 0.4569 with a p-value of 0.0428, representing the only statistically significant relationship identified in the study. This finding demonstrates that increased model complexity and capacity can translate to improved performance in financial sentiment analysis applications, justifying the computational overhead associated with larger transformer models.

Statistical Significance and Reliability

The statistical analysis reveals that only RoBERTa Large achieved significance at the conventional α = 0.05 level, with its p-value of 0.0428 providing reasonable confidence that the observed correlation reflects a genuine relationship rather than random variation. The correlation coefficient of 0.4569 indicates a moderate positive relationship, suggesting that positive sentiment increases are associated with higher Bitcoin price volatility as measured by log returns.

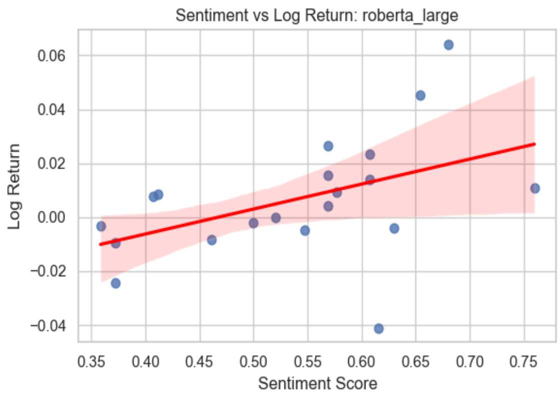

Figure 2. Scatter Plot RoBERTa Large Sentiment vs. Log Return

This finding has important implications for understanding cryptocurrency market dynamics. The positive correlation suggests that increased positive sentiment does not necessarily predict price increases, but rather increased price volatility. This relationship aligns with theoretical expectations that heightened attention and sentiment (regardless of direction) can increase market activity and price fluctuations (GB & B, 2023).

The confidence interval analysis for the RoBERTa Large correlation coefficient provides additional insight into the reliability of the findings. With a 95% confidence interval, the true

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correlation coefficient is estimated to lie between approximately 0.02 and 0.75, indicating substantial uncertainty in the precise magnitude of the relationship while confirming its positive direction.

Methodological Insights and Model Comparison

The superior performance of RoBERTa Large compared to other methodologies provides several important insights into the application of natural language processing techniques in financial analysis. First, the results demonstrate that model scale and complexity can significantly impact performance in specialized domain applications. The larger parameter count and more extensive training data used in RoBERTa Large appear to provide crucial advantages in capturing the subtle sentiment patterns present in cryptocurrency discussions.

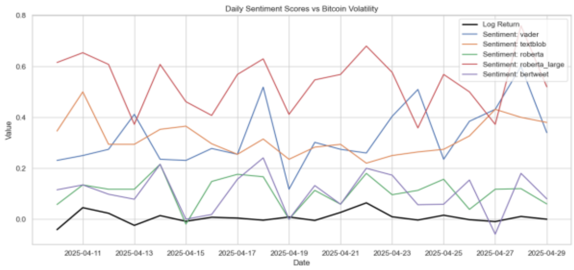

Figure 3. Bitcoin Price and Daily Sentiment Trend Chart

Second, the comparison between BERTweet and RoBERTa models reveals that domain-specific pretraining (such as BERTweet's X-specific training) does not necessarily outperform general-purpose models with superior architecture and scale. This finding suggests that the quality and sophistication of the underlying model architecture may be more important than domain-specific training data, at least within the scope of this analysis.

The gradient of performance improvement from lexicon-based methods through increasingly sophisticated transformer models supports the hypothesis that cryptocurrency sentiment analysis requires advanced natural language understanding capabilities. The informal, context-dependent, and often ironic nature of social media communication about cryptocurrencies appears to benefit from the nuanced contextual understanding provided by transformer-based approaches (Gunasekaran, 2023).

Practical Implications for Cryptocurrency Analysis

The research findings have several practical implications for cryptocurrency market analysis and trading strategy development. The statistically significant correlation identified by RoBERTa Large suggests that social media sentiment analysis can provide valuable information for understanding and predicting Bitcoin price volatility patterns.

For institutional investors and cryptocurrency trading firms, the results indicate that investing in sophisticated sentiment analysis infrastructure, particularly transformer-based models, may provide competitive advantages in market analysis and risk assessment. The moderate correlation strength suggests that sentiment should be considered as one component of a multifactor analysis framework rather than a standalone predictive tool.

For individual investors, the findings suggest that monitoring social media sentiment trends may provide insights into potential periods of increased market volatility, enabling more informed timing of trading activities and risk management decisions. However, the complexity of implementing transformer-based analysis may limit the practical applicability for individual investors without access to specialized computational resources. (I Gusti Ngurah Agung Dananjaya et al., 2025) found that retail investors heavily rely on social media platforms for investment information, with their study showing a positive correlation between social media engagement and short-term trading behavior. The research indicates that while social media sentiment can inform individual trading decisions, retail investors often lack the technical infrastructure and expertise necessary to implement sophisticated sentiment analysis models effectively, creating a potential information asymmetry between individual and institutional market participants.

CONCLUSIONS AND SUGGESTIONS

Conclusions

This study successfully identified a statistically significant positive correlation ($r = 0.4569$, $p = 0.0428$) between social media sentiment and Bitcoin price volatility using RoBERTa Large transformer model. The research demonstrates that sophisticated transformer-based approaches substantially outperform traditional lexicon-based methods (VADER and TextBlob) in cryptocurrency sentiment analysis applications.

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The comparative analysis revealed a clear performance hierarchy: RoBERTa Large > RoBERTa Base > BERTweet > VADER > TextBlob, confirming that model complexity and optimization directly impact effectiveness in financial sentiment analysis. The positive correlation between sentiment and volatility indicates that social media sentiment serves as an indicator of market attention and trading activity rather than price direction.

These findings provide empirical evidence that social media platforms serve as aggregation mechanisms for market sentiment, creating observable patterns that correlate with actual market behavior. The results contribute to behavioral finance theories emphasizing the role of investor psychology in cryptocurrency market dynamics.

Suggestions

Future research should extend this analysis through longitudinal studies covering multiple market cycles to validate the stability of sentiment-volatility relationships over time. Additionally, implementing multilingual sentiment analysis approaches could capture global market sentiment more comprehensively, while exploring temporal dynamics using high-frequency intraday data would provide insights into the speed and persistence of sentiment effects on market behavior.

For practitioners in cryptocurrency markets, institutional investors should integrate transformer-based sentiment analysis as one component of multifactor investment frameworks rather than relying on it as a standalone predictive tool. Cryptocurrency exchanges and trading platforms should invest in real-time sentiment monitoring systems for enhanced risk management capabilities, while individual investors should utilize sentiment-based analytical tools while acknowledging the computational complexity limitations that may create information asymmetries.

Policymakers and regulatory authorities should develop appropriate regulatory frameworks that account for social media influence on market stability and implement market surveillance systems capable of monitoring sentiment-driven volatility patterns. Additionally, consideration should be given to investor protection measures that address potential sentiment manipulation risks in cryptocurrency markets, ensuring the continued development of efficient and stable digital asset markets.

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