Synergy Analysis on Cryptocurrency Returns and Investor Sentiment Using Bidirectional Encoder Representations from Transformers (BERT)

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Article Info
Article history:
Received Nov 3rd, 2024
Revised Feb 2nd, 2025
Accepted Mar 20th, 2025

Keyword:
BERT
Cryptocurrency
Deep Learning
Sentiment Analysis

ABSTRACT
Cryptocurrencies have become prominent alternative investments. Unlike traditional financial assets, their intrinsic value is a subject of ongoing debate since they do not have a tangible backing asset. As a result, investor sentiment heavily influences price volatility and serves as a key indicator of perceived value based on collective investor beliefs. However, major events such as the FTX scandal can severely weaken investor confidence. Social media drives market discussions, making sentiment analysis vital for understanding behavior and predicting price movements. This study examined sentiment analysis techniques to construct an investor sentiment index and investigate its relationship with cryptocurrency returns during the FTX collapse. We employed DistilBERT and the AFINN lexicon method to develop sentiment index, finding that DistilBERT achieves an F1-score of 76.49%, significantly outperforming AFINN's 30.65%. Furthermore, our results indicate a positive correlation between investor sentiment and cryptocurrency returns during the FTX collapse. Our findings indicate that deep learning models can be more effective than lexicon-based approaches for sentiment analysis in financial markets.

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DOI: http://dx.doi.org/10.24014/ijaidm.v8i2.33315

1. INTRODUCTION

The 2008 financial crisis has challenged society's thinking about a centralized transactions system. [1] has proposed a novel way of verifying transactions with cryptographic proof, that may enable the system to become decentralized. Since then, the use of cryptocurrency has been widely adopted. IMF’s data also shows that the crypto market capitalization has become trillions of dollars, as well as the risk-adjusted return has significantly outperformed traditional financial assets such as S&P 500 index and US real estate [2]. However, one of the main driving factors on cryptos’ value is public sentiments, which makes the crypto price movement volatile, as [3] argues crypto has value only just because of public enthusiasm. Several other studies [4]–[6] also found that investor sentiment, especially in online media, can be a proxy for driving crypto returns.

As social media has been embedded in our everyday lives. Due to their fast and cost-effectiveness, social media platforms have been widely used by researchers, professionals, and enterprises to acquire users’ opinions [7]. Several studies from [8], [9] also demonstrated social media provides more collective insights and less biased opinions in comparison to traditional methods such as polls and surveys. Moreover, popular social media platforms like Twitter have a large and active user base. Although Twitter has character limitations per tweet, hence lots of users represent their emotions through emoticons [3]. Other researchers [4], [10] alternatively suggest the Reddit platform as a source of data due to publicly available access through

Pushshift API, up to 10.000 characters per comment, and topics specifically distinguished by subreddits. Reddit users are also identical to young technology enthusiasts, which have relatively easy to adopt new technologies such as cryptocurrency or non-fungible tokens (NFT). Thus, social media platforms can be the proxy for gathering public opinion.

On the other hand, vast amounts of textual data are barely heavy to manually assign the sentiment for each social media post. Hence, via natural language processing (NLP), it automatically identifies which comments are “neutral”, “positive”, or “negative”. For example, lexicon-based methods have pre-label words assigned with a sentiment. [11], [12] has conducted sentiment analysis by positive and negative words in a sentence, resulting in a significant relationship between investor sentiment and stock returns. Later, [13] made a unique domain-specific lexicon based on cryptocurrency corpus that includes terms such as “hodl”, “moon”, and “tulip mania”. Another approach is by using supervised learning, which creates a model that can learn patterns of sentiment. [14] used Naive Bayes algorithms (supervised learning approach) to classify over 1.5 million comments on Yahoo! Finance and Raging Bull. A further method is recurring neural networks (RNN), which can extract the context of the full whole text data rather than focusing only word by word. [15] utilized an RNN-based model to classify cryptocurrency sentiment on the Reddit platform. Even so, due to its simplicity of use, inclusion in several libraries, and superior empirical outcomes across a wide range of disciplines, the Bidirectional Encoder Representations from Transformers (BERT) based model swiftly gained popularity after its release in 2019 [16].

BERT has been extensively researched in NLP, and studies have shown that it performs better in text classification than conventional machine learning models [17]. Bidirectional models like BERT, XLNet, and RoBERTa outperform unidirectional models like GPT and GPT-2 in learning commonsense knowledge, according to another study [18]. On the contrary, [19] has integrated BERT’s contextual semantic with TF-IDF keyword feature enhanced Chinese based language text classification performance compared to LSTM, CNN, and the standard BERT model. In the financial domain, BERT enhances financial sentiment analysis using bidirectional embeddings and a dataset of 5,842 samples from FiQA and the Financial PhraseBank [20]. [21] fine-tune BERT on a manually labeled dataset of 582 financial news articles to analyze sentiment, achieving a 72.5% F-score, and demonstrate its potential to predict Dow Jones Industrial Index movements, aiding rapid decision-making in volatile markets. However, like most deep learning models, BERT demands substantial computational power. Therefore, [22] introduced DistilBERT, a lightweight version of BERT that reduces the number of layers by half. Study from [23] has employed DistilBERT for analyzing football fan sentiments on Twitter, achieving 92.56% test accuracy on the 2018 FIFA World Cup dataset, with Random Forest emerging as the most robust classifier. [24] chose DistilBERT for its 60% faster performance, comparing sentiment analysis tools and revealing a strong 0.88 correlation between sentiment and Bitcoin prices, confirming Bitcoin's dominance. Although DistilBERT is a lightweight model, a study by [25] shows that BERT achieves only slightly higher F1-score (0.84-0.87) compared to DistilBERT (0.83-0.85), but requires 58.6 minutes for training, whereas DistilBERT is significantly faster at 25.6 minutes.

We use social media as a proxy to measure investor sentiment, as [3] shows that investors get positive returns when sentiment on the Reddit platform is bullish, and argues that crypto prices are undervalued when investor sentiment is low. In addition, a study from [4] concluded that online platforms such as Reddit and Wikipedia play a significant role in the investment decision process, where there is a similar pattern between information volume and trading volume. On the other hand, social media provides thousands of comments daily which makes it difficult to label each comment manually. Therefore, we propose a deep learning method to predict the sentiment of each social media comment on a specific crypto asset. Consequently, we construct a daily sentiment index from labeled comments and correlate its movement to the daily returns of crypto assets.

Recently there has been a major event that may have shrunk the confidence in crypto assets, the FTX’s trading exchange collapsed. FTX was the third largest cryptocurrency exchange platform, with over $10 billion trading volume and valued at $32 billion [26]. However, as reported by [27], there were eight issues found, which are (i) misuse of consumer funds to finance an affiliated company, Alameda Research, (ii) conflict of interest, (iii) use FTT token as the collateral loan, (iv) concentrated portfolio, (v) absence of corporate governance, (vi) lack of financial reporting records, (vii) limited due diligence by the investor, private equity and venture capital, and (viii) inadequate risk management policy. When this scandal was announced, it drove investors feeling deceived, and uncertain about the future of FTX which led to their crypto assets’ withdrawal.

As FTX was one of the leaders for each sector, the impact was quite devastating for cryptocurrency’s image as an alternative to the centralized system. Moreover, to our best knowledge, research on crypto assets is still thriving and many studies have been conducted with bonds or stocks as an object. This study contributes to academic research in the following ways: (1) it enhances the existing literatures by providing an analysis of both traditional machine learning and deep learning approaches for sentiment analysis within the financial domain, and (2) it examines the interplay between cryptocurrency returns and investor sentiment during the collapse of FTX, providing insights into their dynamic relationship.

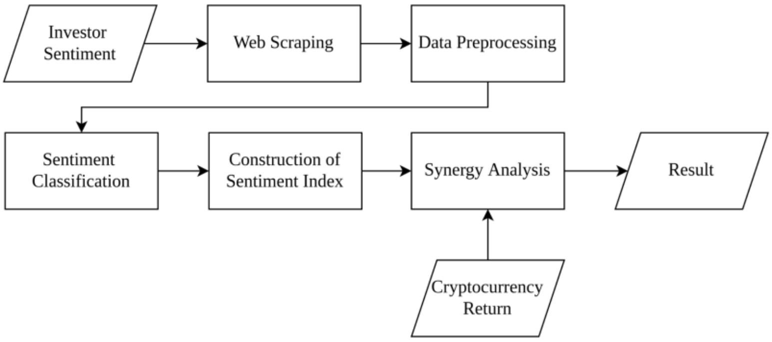

Figure 1. Research Methodology

2. RESEARCH METHOD

In this section, As appeared in Figure 1, the authors present the following steps to conduct the research. At first, the data was collected by web scraping from the Reddit platform. In the second step, the sentiment index is built by grouping the predicted sentiment into daily time-series data. Third, the Pearson correlation was applied to the daily sentiment index and cryptocurrency return to find the synergy level between the two variables. The details of the following steps will be explained in the following subsections.

2.1 Data Collection

This study analyzes the context of FTX's collapse period, which appeared on September 12, 2022 to February 10, 2023. As objects of the research, we chose four cryptocurrency assets based on the largest market capitalization in 2022. Based on CoinMarketCap, the assets are Bitcoin, Ethereum, Binance, and Cardano. Those assets were equivalent to more than 70% of the cryptocurrency market capitalization. To conduct synergy analysis, two main data sources have been data employed. First, the investor sentiment data was gathered from Reddit platform, specifically on "r/Cryptocurrency" subreddits. Using scraping techniques with Pushshift API library, we gathered 798,071 comments on the "r/Cryptocurrency" subreddits as presented on Table 1. Second, the daily cryptocurrency prices were obtained from Investing.com. However, our crawled data was unlabeled, so we use publicly available dataset to train our sentiment analysis model. Therefore, we merged Bitcoin Reddit Sentiment Dataset (BRSD) [28] and Crypto Sentiment Dataset (CSD). We chose those datasets based on a similar source of data, Reddit social media platform. Moreover, BRSD dataset has already been pre-processed such as removed bot detected comments, eliminated moderated contents, and consist of multiple subreddits sources.

Table 1. Sample of Collected Data

Subreddit	User Comment	Datetime (UTC+0)
Cryptocurrency	My bad 😔	2023-02-01 23:48:14
Cryptocurrency	Too bad it still need to 10x for most people to break even lol CryptoCurrency	2023-02-01 23:45:14

2.2 Bidirectional Encoder Representations from Transformers

BERT is a deep learning model built on the idea of extracting information from a pre-trained model that has been applied to related or auxiliary tasks, either by employing a model's fixed outputs or by fine-tuning the original model to a new task [29]. The model architecture grounded upon the Transformer encoder structure proposed by [30], while omitting the decoder component. The BERT's essential aspect is its bidirectionality, since it captures numerical representation from the surrondings word from right-to-left and left-to-right, so it enchances the sentence or word contextual meaning [31]. It also embeds the attention mechanism, which allows model to prioritize on more important part of the sentence, the computation is shown on Equation 1 [30].

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left[\frac{QK^T}{\sqrt{d_k}}\right]V \quad (1)$$

Based on the same principle, [22] explored distilled version of BERT, called DistilBERT which reduces the model size by 40%, while being 60% faster. The compressed and swift model reduces the needs of computational resources, which optimizes the fine-tuning or other application cost. Knowledge distillation was the technique that is used to train the DistilBERT in teacher-student architecture, which the DistilBERT (student) tried to mimic the BERT (teacher) action [32]. DistilBERT has only 6 transformer layers and 2048 hidden units in constrast with BERT model, which has 12 transformer layers and 7132 hidden units [32]. The DistilBERT architecture can be seen in Figure 2.

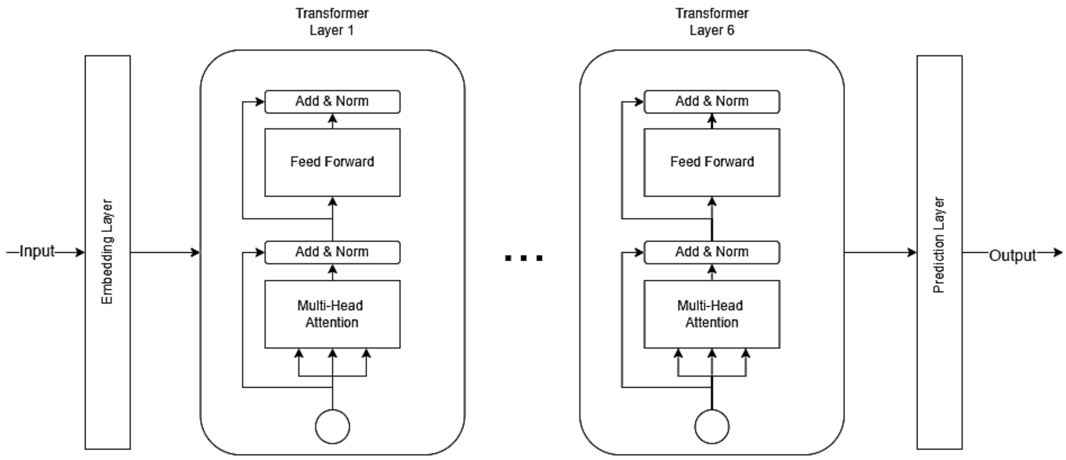

Figure 2. DistilBERT Architecture [32].

2.3 Investor Sentiment Analysis

Given 798,071 data can be quite challenging to classify each comment manually. Hence, the text classification approach using natural language processing can be an alternative way to minimize time and cost. On the other hand, our dataset was quite unique, since it consists of informal interaction or opinion on Reddit's platform. Based on study by [13], the user interaction on related cryptocurrency social media were unique, due to slang terms that are used. Therefore, we used a model that was specifically trained on cryptocurrency social media terms.

Besides that, we chose Bidirectional Encoder Representations from Transformers (BERT) as our model. BERT is a deep learning model built on two stages of training, (i) the first one is to create language model based on masking random words in sentences, then the goal is to predict the masked word, and (ii) second stage more focus on creating model on specific tasks such as sentiment analysis, topic modeling, and etc. For that reason, BERT based can extract the context of the sentence, rather than focusing on word by word. We also compared our model to a relatively traditional method such as lexicon-based approach. After that, the classified Reddit comments were being grouped to construct a daily sentiment index, which the procedure is being described in the following parts.

2.3.1 Investor Sentiment Analysis

The massive scale of social media data can be unreliable due to informal or slang language and data duplication. Therefore, data cleansing methods are used to standardize the format and enhance text quality. Our preprocessing steps included lowercasing every comment, removing all duplicate comments, taking out deleted or removed comments, and excluding comments that are being moderated by Reddit’s admin. In the final steps, we used a pre-trained distilbert-base-uncased AutoTokenizer module to preprocess each comment in the dataset.

2.3.2 Sentiment Classification

This subsection focused on developing sentiment classifiers, which has three classes, “negative”, “neutral”, and “positive” sentiments. We used two approaches, which are lexicon-based methods and deep learning models. We chose AFINN corpus as our lexicon-based classifier based on [33] and [34] prior study on relationship between cryptocurrency and investor sentiment. As mentioned earlier, we chose the BERT based model due to their capability of recognizing context in the sentences. However, due to limited resources, the Distilbert model was chosen as it offers a significantly lower number of parameters but still has competitive performance. [35] suggests to use 2e-5 learning rate and 0.01 weight decay as the hyperparameters. We trained Distilbert models on eight epochs and also cross-validated using k-fold to check our model robustness. Lastly, since our dataset was imbalanced, we use stratified random sampling to ensure the class distribution of trained dataset.

2.3.3 Construction of Sentiment Index

Daily expressed investor sentiment was aggregated by Antweiler's methods to construct the investor confidence index (ICI), which can be seen on Equation 2. ICI measured the bullishness index by comparing a number of positive sentiments (N^{Pos}) and negative sentiments (N^{Neg}) within time t. Hence, optimistic market confidence is indicated by a higher proportion of positive sentiments. On the other hand, a higher ratio of negative sentiments indicates collectively pessimistic market confidence within the given period. However, the ICI is expressed as follows.

$$\mathrm{ICI_t} = \ln\left[\frac{1 + \mathrm{N_t^{pos}}}{1 + \mathrm{N_t^{neg}}}\right] \tag{2}$$

2.4 Synergy Analysis

Synergy between two variables can be measured by the correlation of those variables. Positive synergy means the movement of a given variable positively correlates with another and vice versa. As stated on Equation 3, the synergy index at a given period (SI_p) is described as the coefficient of the correlation between the investor confidence index (ICI_t) and the log return of cryptocurrency (R_t) at a time t. Calculating the correlations has multiple approaches such as regression, Pearson's correlation, Spearman's correlation, and Kendall's correlation. A study from [36] suggests no significant differences between those methods. Hence, we chose the straightforward and efficient approach, Pearson's correlation.

$$\mathrm{SI_p} = \mathrm{Pearson}(\mathrm{ICI_t}, \mathrm{R_t}) \tag{3}$$

For that case, the full samples of the synergy index (SI_{Full}) in the FTX case are the coefficient of correlation between ICI and the log return of cryptocurrency from September 12, 2022 to February 10, 2023. We also analyzed the behavior within smaller periods, by dividing the full sample period into the period before the case happened (SI_{p-1}), period where the case happened (SI_{p0}), and period after the case happened (SI_{p+1}) as visualized on Figure 3. The separated samples period was symmetrical in reference to [36]'s study. Those periods are based on FTX's collapse timeline, which occurred on November 2, 2022 to December 22, 2022 or equivalent to 51 days. Since the periods were meant to be symmetrical, the SI_{p-1} will be on September 12, 2022 to November 1, 2022. On the other hand, SI_{p+1} will be on December 23, 2022 to February 10, 2023.

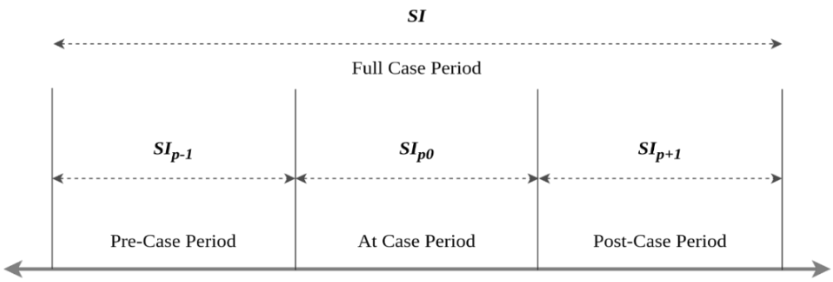

Figure 3. Separation of Each Sample Period

3. RESULTS AND ANALYSIS

3.1 Reddit Sentiment Analysis Model

We use publicly available labelled dataset from Bitcoin Reddit Sentiment Dataset (BRSD) and Crypto Sentiment Dataset (CSD). The datasets were utilized to evaluate the performance of both the AFINN lexicon-based method and our deep learning model. Additionally, the trained model was employed for sentiment analysis, which was subsequently used to construct a sentiment index. BRSD and CSD dataset consisted of 37,695 comments, which can be broken down into 17,037 negative labels, 8,448 neutral labels, and 11,587 positive labels. The train and validation set distribution was 80% and 20%, as we also used k=5 for the cross-validation method. Since we used stratified random sampling, for each k consists of 45.96%

negative labels, 22.79% neutral labels, and 31.25% positive labels. Due to this imbalance distribution, we chose F1-score rather than accuracy as our evaluation metric.

Table 2. Result of Sentiment Classification on BRSD and CSD

	AFINN	Our Model (Distilbert)
k	F1-Score	
1	31.06%	75.42%
2	30.90%	75.77%
3	30.63%	73.73%
4	30.15%	77.44%
5	30.49%	78.31%
Average	30.65%	76.49%

Table 2 shows the benchmarking result of two approaches on BRSD and CSD. We trained the model using the Transformers module by Hugging Face on NVIDIA RTX 4080. Our models consistently outperformed the AFINN method on every k group. On average our models resulted in 76.49% on F1-score, while the AFINN was only 30.65%. Based on this result, we used the Distilbert model as our sentiment classifier for constructing the sentiment index.

3.2 Synergy Analysis on FTX Case

Our second analysis was concerned with investigating the FTX event timeline. Most of the sentiment scores before pre FTX period more than zero, which implies the number of daily positive sentiment exceeds the negative sentiments. The circumstance timeline is shown on Figure 4, as the line marks the investor sentiment (ICI) score and dotted lines labeled the event happened. In general, pre FTX's collapse period, marked by before (a), the public sentiments were positive, while significant drop occurred in (a-i) FTX's collapse period, and rebound after (i) the following period.

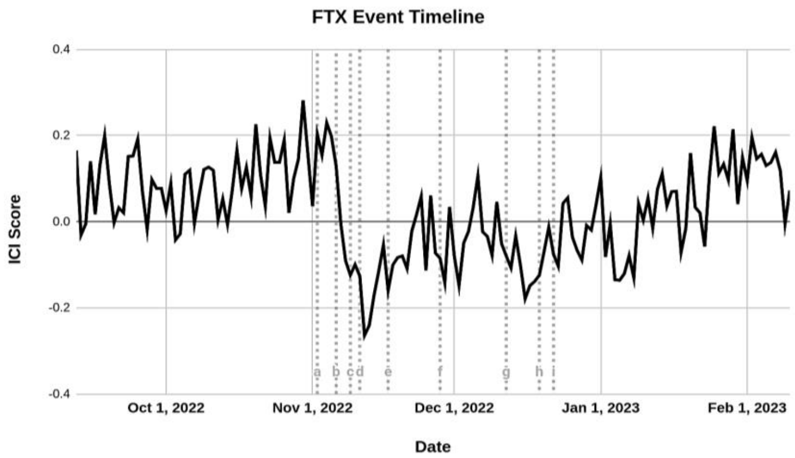

Figure 4. FTX Event Timeline Based on [37]

Based on [37], dotted lines underline events occurred during the period: (a) November 2, 2022 was the beginning of the collapse, as a financial document of Almeida Research, FTX Founder's trading firm was being leaked. Moreover, on (b) November 6, 2022, Binance's CEO, Changpeng has announced the liquidation of the FTX token, FTT. Consequently, it triggered negative responses from the investor as drops shown by early November as Figure 3 is shown. Response to Changpeng's announcement, Sam Bank Friedman (SBF) denied the rumor and said the FTX was fine, while Changpeng offered an acquisition proposal to SBF. On (c) November 9, 2022, Binance pulled out acquisition offers after a due diligence issue. However, on (d) November 11, 2022, FTX filed a bankruptcy document and along with that SBF resigned as CEO, while being replaced by John Ray III. As the new CEO, John Ray III marked historical comments "Never in my career have I seen such a complete failure of corporate controls and such a complete absence of trustworthy financial information as occurred here." on (e) November 17, 2022. By (f) November 28, 2022, BlockFi, a crypto lender firm filed for bankruptcy. On the date of (g) December 12, 2022, SBF was arrested by US authorities in the Bahamas. In the following week, (h) December 19, 2022, Executives from FTX and Alameda have admitted to fraud. Lastly, on (e) December 22, 2022, SBF was released after a $250 million bail out fee.

Table 3. Synergy Result in FTX Case

	Bitcoin	Ethereum	Binance	Cardano
SI_{Full}	0.182*	0.135*	0.214*	0.152*
SI_{p-1}	0.095	-0.019	0.076	0.056
SI_{p0}	0.230	0.207	0.286*	0.275*
SI_{p+1}	0.190	0.203	0.097	0.114

Note: * indicates stastistical significance.

The synergy index results within the period in FTX are reported in Table 3. The synergy index between 12 September 2022 and 10 February 2023 ranges from 0.077 to 0.214, which implies very weak positive synergy, besides the Binance which has weak positive synergy. Moreover, all of the studied assets are statistically significant. Based on that result, we suggest that investor sentiments on Reddit platform are synergized with crypto assets returns.

We also broke down our analysis into three symmetrical periods of time, pre FTX's collapse period, at FTX's collapse period, and post FTX's collapse period. In the pre FTX's collapse period, we found all of the assets were at very weak synergy with no statistically significant results. However, our results showed that there has been an increase of synergy index magnitude at the FTX's collapse event, while the decreasing synergy value after the following period.

3.3 Results Discussion and Broader Implications

Based on our experiments utilizing stratified sampling and cross-validation, DistilBERT demonstrates superior performance on F1-score compared to the AFINN lexicon-based method. We argue that the AFINN model was not suitable for our dataset, since the terms that are used in social media, especially cryptocurrency, differ from daily used English corpus. [13] also mentions Reddit has their specific terms of languages that refers to certain sentiment such as "to the moon", "shitcoins", "scam coin", and "hodl". Moreover, lexicon-based approach only rewards the frequency of negative or positive words that appear. Besides, complexity of human languages is not limited to good or bad words in the sentences, rather than the context of the sentences itself. Hence, the BERT based model can be a suitable solution as it can get the context of the sentences by extracting positional and sentence embedding. Those embeddings are the representation of the words before and the words after, so the same word can have different embedding as it refers to the surroundings. Aligning with [38], AFINN excels in short reviews but lacks contextual depth, while DistilBERT's transformer-based model effectively captures complex word-context interactions, making it superior for sentiment analysis in longer reviews, such as Bangladeshi food delivery app feedback.

Conversely, our findings suggest that investor sentiment on the Reddit platform interacts synergistically with cryptocurrency asset returns in the time of FTX's collapse period. [39] found that savvy investors respond quickly and harshly to the announcement of accumulated bad news at FTX's collapse period. While in the post FTX's collapse period, investor confidence seems to be rebound as sentiment scores are relatively increasing, as study by [39] found markets are stabilized after the FTX's announced its bankruptcy. Other studies from [39] and [40] also support our findings, as stated Bitcoin, Ethereum, and Binance responded significantly negatively and other cryptocurrency assets had contagion effects at the time of the event. At the time of the scandal made investors become pessimistic about the future of cryptocurrency, as it is not only backed up by any physical assets. Moreover, private companies acting as trading exchanges broke fundamental promises, secure transactions without third party approval. Therefore, FTX's collapse set a separate pathway for cryptocurrency to become more heavily regulated centralized finance (CeFi) or decentralized finance (DeFi) by ensuring self-governance and on-chain transactions.

Our findings suggest that deep learning methods, such as DistilBERT, may be considered as a potential approach for sentiment analysis tasks on social media platforms. However, there are several recommendations for future research. Since our study utilizes open-source datasets such as BRSD and CSD, we suggest that future studies manually label the Reddit dataset to enhance data quality. Additionally, we performed data cleansing to remove duplicate entries. Moreover, we did not fine-tune the hyperparameters for DistilBERT training due to computational constraints. Therefore, we recommend that future research explore hyperparameter tuning to potentially improve model performance.

4. CONCLUSION AND FUTURE WORK

Our findings indicate that DistilBERT achieves an F1-score of 76.49%, whereas AFINN attains an F1-score of 30.65% in sentiment classification on a Reddit platform. This highlights the superior performance of transformer-based deep learning models over lexicon-based approaches in this context. Our study highlights that the AFINN lexicon is not suitable for capturing cryptocurrency investor interaction, as the terms that are used differ from daily used English. Using a trained deep learning model, we developed sentiment index to measure synergy between investor sentiment in social media along with cryptocurrency returns at the event of FTX's downfall period. Based on the DistilBERT model, we calculated correlation between investor confidence index and crypto assets return. We found that investor sentiment and cryptocurrency return significantly have a synergistic relationship at the FTX's failure.

Based on the performance of DistilBERT, there is still room for improvement in enhancing the model's performance, especially on F1-score. In this study, we did not perform hyperparameter tuning, which could further optimize the results. Additionally, we recommend that future research focus on developing custom datasets, as this would improve the robustness and reliability of sentiment classification by introducing better checks and balances in data quality.

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