

## Research Article

# Predicting Price Trends Using Sentiment Analysis: A Study of StepN's SocialFi and GameFi Cryptocurrencies

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**Abstract:** The cryptocurrency market, specifically the non-fungible token (NFT) market, has been gaining popularity with the rise of social finance, game finance, metaverse, and web 3.0 technologies. With the increasing interest in cryptocurrency, it is essential to develop a comprehensive understanding of the market dynamics to aid investment decisions. This paper aims to analyze the impact of news sentiment on the prices of two cryptocurrencies, Green Satoshi Token (GST) and Green Metaverse Token (GMT). The sentiment analysis model used in this study is Finance Bidirectional Encoder Representations from Transformers (FinBERT), a pre-trained deep neural network model designed for financial sentiment analysis. Additionally, we introduce the use of the Extreme Gradient Boosting (XGBoost) algorithm to evaluate the sentiment result on the model's performance. The study period covered from March 2022 to April 2022, and the sentiment score of the result generated by FinBERT on crypto, stock market, and finance news was found to be correlated with the prices of GST and GMT. The findings suggest that the sentiment score of GST reflects changes in the price earlier than GMT. These findings have significant implications for decision-making strategies and can aid investors in making more informed decisions. The research highlights the importance of sentiment analysis in understanding the market dynamics and its potential impact on the prices of cryptocurrencies. The use of FinBERT and XGBoost algorithms provides valuable insights into market trends and can aid investors in making informed decisions.

**Keywords:** cryptocurrency, sentiment analysis, machine learning, fintech, investment

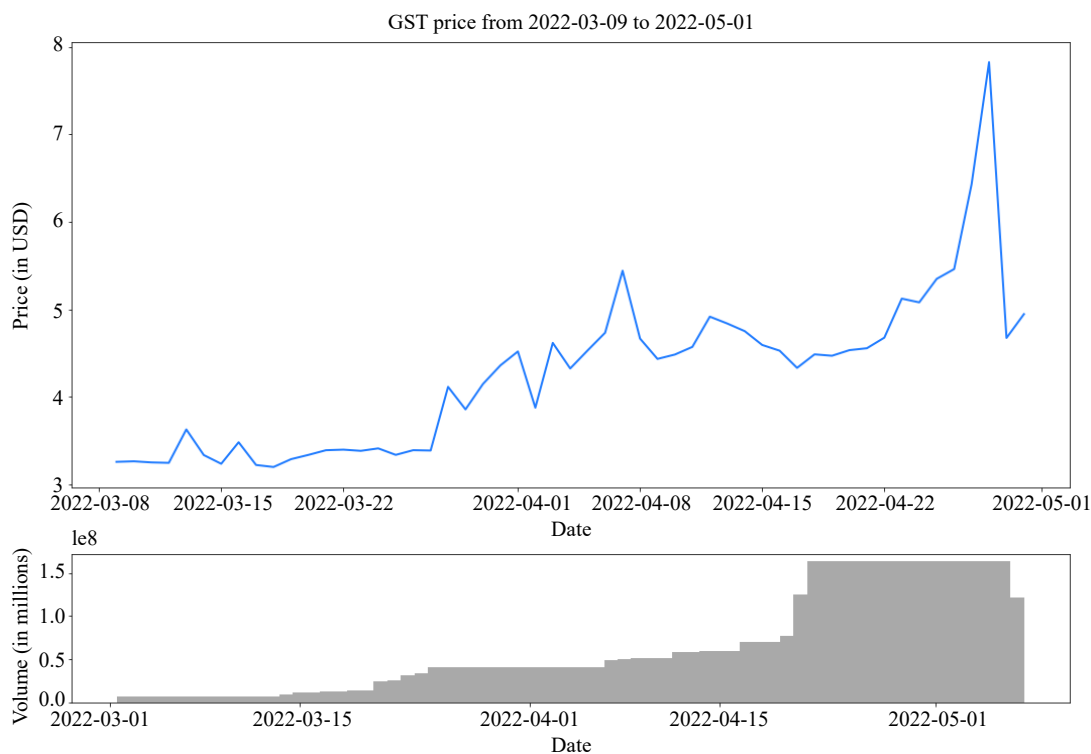
**MSC:** 68T50

## 1. Introduction

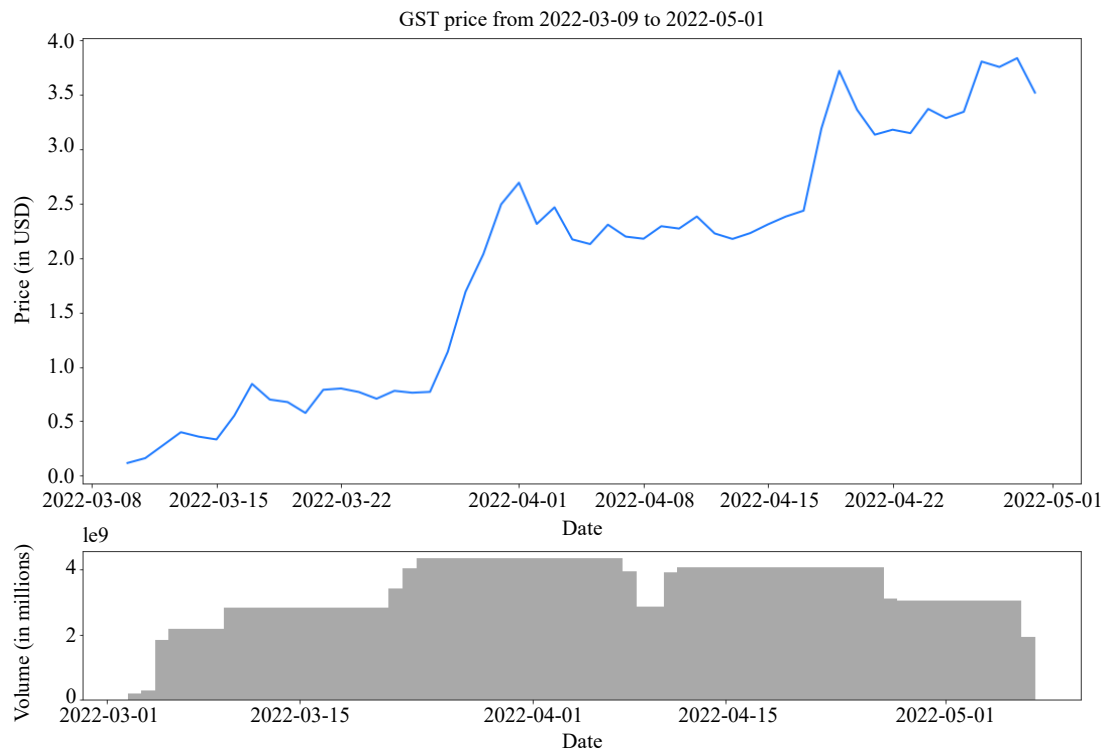
Social finance, also known as SocialFi, is an innovative concept that involves combining social networking and financial services on the blockchain [1]. The aim is to provide users with benefits and rewards by tokenizing and financializing social influence. StepN is an example of an application that leverages innovation to transform SocialFi [2]. This unique application combines game finance (GameFi) and SocialFi to create a new and exciting concept that is gaining popularity, particularly in Southeast Asia. GameFi is a new trend that allows players to earn cryptocurrency through playing games, and applications like Axie Infinity and DeFi Kingdoms have helped to propel this concept to new heights. StepN focuses on movement, such as walking or running, as a way for users to earn cryptocurrency. It

was awarded fourth place out of over 500 proposals at the Solana Ignition Hackathon in 2021, and users can earn non-fungible tokens (NFTs) in the form of sneakers to exchange for the platform's Green Satoshi Token (GST) and Green Metaverse Token (GMT) [2].

This research focuses on the influence of news related to crypto, stock market, and finance on market sentiment and investor decisions. Therefore, news related to these topics could potentially have an impact on the market and are relevant to this study. Examples of such news include announcements of new cryptocurrency regulations, corporate earnings reports, global economic indicators, geopolitical events affecting financial markets, and other similar developments. In the past, some investors have utilized their expertise in the GameFi concept to make informed decisions about market sentiment and price changes. By conducting diligent studies, they were able to manually read news and analyze the market, allowing them to make better decisions and earn sizable profits from gaming related to GameFi. Therefore, the same approach is applied to StepN, but with a more automated method that utilizes sentiment models and artificial intelligence (AI). For example, updates on StepN's airdrops or changes to its rewards system can significantly impact the demand for its coins, including GST and GMT. Between March 9, 2022, and May 1, 2022, the prices of GST and GMT reached all-time highs of 244% and 3,265%, respectively, as shown in Figures 1 and 2. If AI can accurately detect this type of news and make informed decisions, investors can potentially earn significant profits. By analyzing vast amounts of data in a short period of time, computing engines can help investors react and respond more quickly. In this study, we aim to evaluate the scientific validity of different types of news for sentiment analysis and how they can influence crypto pricing.



**Figure 1.** Source from Yahoo Finance: GST price min USD 3.2 jump up all time high at price USD 7.82 approximately 244% during March 9, 2022 to May 1, 2022



**Figure 2.** Source from Yahoo Finance: GMT price min USD 0.117 jump up all time high at price USD 3.83 approximately 3,265% during March 9, 2022 to May 1, 2022

The lack of knowledge and understanding makes it challenging for major investors to invest in the crypto market. The crypto market is a fast-paced, 24/7 active market that poses considerable risks even for systematic investments, despite the possibility of higher earnings [3]. Anticipating the fluctuations in the market to make money is a challenge for even the most experienced investors. Therefore, effective approaches to detect price changes due to the influence of news are crucial. News has a significant impact on the cryptocurrency market, and it can change at any time. Thus, it is important to keep a regular eye on the market to stay up to date with the latest developments. However, manually monitoring news and market changes is difficult for a normal investor to identify.

When deciding to invest in cryptocurrency, several factors need to be considered, for instance, recent cryptocurrency news, the integration of smart contracts such as Ethereum (ETH), Solana (SOL), and Binance (BNB) into future projects, and the impact of government legislation on the cryptocurrency market in different countries. News, social media, and forums can provide valuable insights into how the market reacts to certain events, particularly economic news, and how this may impact cryptocurrency values [4]. However, acquiring relevant data can be challenging due to the scarcity of publicly available accurate data, and analyzing the data requires significant human effort to collect and analyze.

This study aims to explore the potential integration of crypto technology into investment strategies by identifying the variables that influence investors' risk-taking behavior and the obstacles they face. The crypto market is still young and highly risky, which makes it crucial to incorporate psychological factors into trading strategies. To predict future trends, sentiment analysis can be used in conjunction with other forms of analysis such as quantitative, technical, and fundamental analysis [5]. Market sentiment analysis can be an effective way to incorporate the psychological influences of investor sentiment into trading strategies. It is essential for investors to exhibit reasonable behavior patterns, particularly in behavioral finance, in order to overcome their tendencies towards irrational or biased investment decisions when buying or selling in trading [6, 7].

An understanding of how investors, gamers, and creators interact can help researchers determine the profitability of a system. Predictive trends may indeed be defined by analyzing the strengths and weaknesses of cryptocurrencies prior to using sentiment analysis and AI. The Finance Bidirectional Encoder Representations from Transformers (FinBERT) model [8] was used to identify "positive" and "negative" scores from financial news and community discussion and

announcements. This model is a sentiment analysis technique that is essential to creating the polarity of the score. Later, the classification can be integrated with a predictive model like Extreme Gradient Boosting (XGBoost) to generate predictive trends that recommend potential directions [9].

## 2. Related works

As the crypto market continues to grow, the number of crypto enthusiasts and wallet addresses has surpassed 100 million, according to CoinDesk [2]. For investors, it can be challenging to make informed decisions about which coins or tokens to invest in, particularly with so many to choose from. To invest, one of the methods is to apply sentiment analysis and AI algorithms to identify trends. This is an emerging strategy decision-making technique that investors can use to make data-driven decisions, particularly when predicting crypto trends based on social media and financial news data [4]. Opinion mining, or sentiment analysis, can help gather data about what people think and feel about a particular subject of interest [10]. Understanding market sentiment and direction is crucial for making informed decisions about whether to buy or sell crypto. The study's significance lies in the fact that current research on cryptocurrencies is limited, with a focus on sentiment analysis in the stock market. Furthermore, research on SocialFi and GameFi-linked crypto is even more limited. The goal of this paper is to fill this gap by applying sentiment analysis to establish a unique paradigm for investing in SocialFi and GameFi-linked crypto, such as StepN.

Investing in the crypto market may be difficult and unfamiliar for new investors, especially in an emerging market like crypto. When it comes to investing in cryptocurrencies, investors have no idea which one to buy or sell, making it difficult for them to make a clear investment decision. Based on the efficient market hypothesis (EMH), cryptocurrencies show behaviors similar to stock market behaviors. Hence, cryptocurrency investment depends on accurate information and an efficient market [11]. For their trading to be efficient, they need to have access to the most recent crypto market news and information, as well as the ability to get this information near where they can get it firsthand. The market for cryptocurrency depends on an efficient market, which is enhanced by these developments in predictive trends and sentiment analysis. The findings of this study will be beneficial to investors who are looking to make better decisions on whether to sell or buy cryptocurrencies. By being able to predict the direction of the market, investors can invest at a lower price with the expectation of later selling it for a profit at a higher price. Keeping up with the news and understanding behavioral finance are crucial in forecasting the direction of the crypto market. The study builds upon previous research that shows how the sentiment of news could influence pricing and applies it to the SocialFi and GameFi sectors. This is particularly relevant because breaking news can affect stock indices and other important cryptos, which can ultimately affect the SocialFi and GameFi-linked crypto markets. The research also addresses the challenge of analyzing large amounts of data in a short period of time and identifying trends with high accuracy. This can be overcome by applying the theory and implementation of an AI investing framework and contributing to the development of a more efficient and effective investment strategy for SocialFi and GameFi-linked crypto and potentially the broader cryptocurrency market.

For the natural language processing (NLP) model that we used in this research, we utilized the FinBERT model for generating sentiment scores from the textual data obtained from news and Discord discussions and announcements. FinBERT is a sentiment analysis model that is based on BERT, one of the most successful sentiment models in recent years [12]. BERT was developed by Google and Devlin's team and is an open-source library that has been pre-trained on millions of words from the entire Wikipedia corpus. It predicts masked words using the BERT model and is trained to forecast masked words, which is also known as next sentence prediction. FinBERT is a suitable technique for this research due to its specific focus on the financial and investment domains. FinBERT is a specialized version of the BERT model that has been fine-tuned to perform sentiment analysis specifically for financial and investment-related texts [13]. It has been pre-trained on a large corpus of financial text data and then fine-tuned on a smaller set of financial data for sentiment analysis. This allows it to capture the nuances of financial language and provide more accurate sentiment scores for financial text data.

In the realm of price trend prediction, researchers often consider utilizing NLP models to generate sentiment scores that can be used to evaluate the influence of various factors on pricing. Once the sentiment scores were generated, we sought to evaluate their efficacy by comparing prediction models with and without the sentiment scores. The XGBoost model was selected as our machine learning technique for this comparison, as it is known for its efficient and effective

implementation of the gradient boosting algorithm and has been shown to outperform numerous other algorithms. Chen and He [17] recommend XGBoost, citing its ability to be combined with time series models and its compatibility with the Sklearn library. By utilizing XGBoost, we were able to perform model fitting, application, and validation all on the same platform.

### 3. Methodology

#### 3.1 Framework

An investment framework is introduced in this paper as follows: FinBERT can take advantage of sentiment analysis performed on investor reviews provided by the proposed framework. As shown in Figure 3, the steps involving data collection, preprocessing, classification, and predictive are the four pillars of the proposed framework.

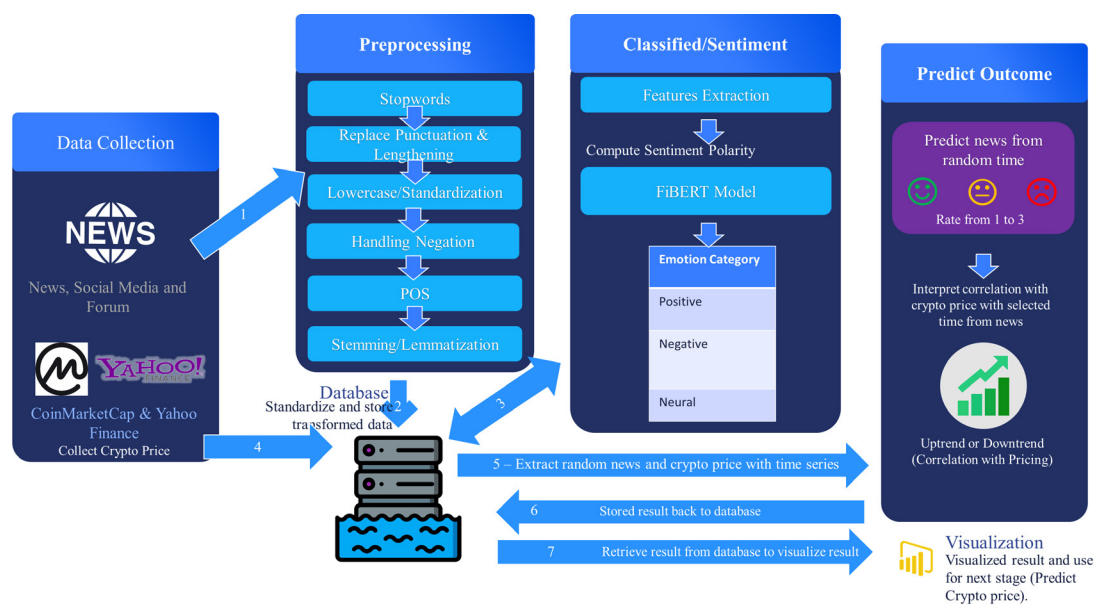


Figure 3. AI investment framework: extracting data, preprocessing data, feature engineering, and classification of NLP for sentiment analysis

Below are the steps, breakdown in detail, to interpret Figure 3:

- Retrieve random news from Forbes that can be used to generate the sentiment score, such as bullish, bearish, or neutral, and categorize it into crypto, finance, and stock market news. In addition, collect StepN’s announcement and discussion group data from Discord.
- To effectively analyze news and Discord data, it is essential to preprocess the textual data to remove noise such as stopwords, punctuation, lowercase, handling negation, and part-of-speech (POS), and to convert the text into a structured format that can be stored in a database or repository.
- After the textual data has been preprocessed and structured, it can be transferred to a machine learning model (FinBERT) to classify the sentiment polarity. The results can be compared to understand the influence on pricing. This can be done by analyzing the correlation between sentiment polarity and cryptocurrency prices. The data and results can be stored in a repository or database for further analysis and reference.
- CryptoMarketCap and Yahoo Finance data extractions are conducted to help address the correlation between sentiment and predictive results. Analyze CoinMarketCap information and Yahoo Finance data and keep it in a repository for later use, such as stock closing price, open price, adjusted price, volume, etc.
- After obtaining the sentiment score result and GST/GMT pricing data in a repository, the next step is to perform a correlation analysis. This involves classifying the news data into different categories, such as crypto, finance,

stock market, announcement, and discussion. The sentiment score of each category can then be compared to the pricing data to understand the influence of pricing. By analyzing this data, we can evaluate the relationship between news sentiment and price trends. To further evaluate the performance of sentiment analysis, we can use the XGBoost prediction model to compare the prediction results with and without sentiment score data. This will enable us to determine whether incorporating sentiment analysis data improves the accuracy of price prediction. By comparing the prediction results, we can determine whether sentiment analysis data can be effectively used to predict cryptocurrency pricing.

- vi. After analyzing the data and evaluating the performance of the XGBoost prediction model with and without a sentiment score, the result will be stored in the repository. This final result will include the correlations between different classified news and their influence on crypto pricing, as well as the performance of the prediction model.
- vii. After storing the final result in the repository, the next step is to visualize the data to gain insights and analyze the result. Visualization can help identify patterns, trends, and relationships in the data that may not be immediately apparent from the raw data.

### 3.2 Data collection

In this section, we will delve into the intricacies of the data collection process, including the sources, methodology, and procedure employed to develop StepN’s sentiment indicator and predictive approach for identifying GST and GMT price trends. A total of 1,510 news articles were collected from Forbes’ Money between March 9, 2022 and April 25, 2022. These articles were further categorized into 193 cryptocurrency news, 972 finance news, and 345 stock market news. In addition, Discord announcement records were extracted from the same duration as news which is March 9, 2022 to April 25, 2022, with 230 records for announcements and 984,972 records for general discussions. While a longer time period of data would be ideal for training and evaluating a sentiment model, one and a half months of data can still provide some insights into the relationship between sentiment and price trends. It may be possible to identify any patterns or correlations that exist during this timeframe, which can be useful in developing a predictive model.

Additionally, the comparison between the XGBoost model with and without a sentiment score can still be done with the available data. This can help determine whether the sentiment score adds any value to the prediction accuracy and inform future decisions on incorporating sentiment analysis into the model. Table 1 summarizes the data collections by source, total number of records, and method used for data collection.

**Table 1.** Summary data collections

Source	Total number records	Method
Forbes’ Money	1,510	Web crawling
Discord announcement	230	Extractor tool
Discord general discussion	984,972	Extractor tool

For data collection from Forbes’ Money, we utilized a web crawling technique using Python Scrapy, as outlined by Najork [15]. This approach enabled us to extract structured data from unstructured web pages. Scrapy uses the Selenium library to extract web pages via their URL and crawls the html value from the targeted URL, allowing us to extract metadata such as title, description, author, and publish date. The news articles were then manually categorized into finance, stock markets, and cryptocurrencies by identifying relevant keywords. Figures 4, 5, and 6 provide a daily breakdown of the collected data from Forbes’ Money. It is important to take into consideration the potential noise and lack of reliability in StepN’s community discussion data collected from Discord. Although it may not be the most reliable source of data, it is still a valuable source for experimentation and gathering insights on trends in the community.

Based on the data collected, the large volume of data from the community discussion (over 7,000 daily records)

suggests that there is a significant level of interest and activity within the community, which can be useful information for investors and analysts.

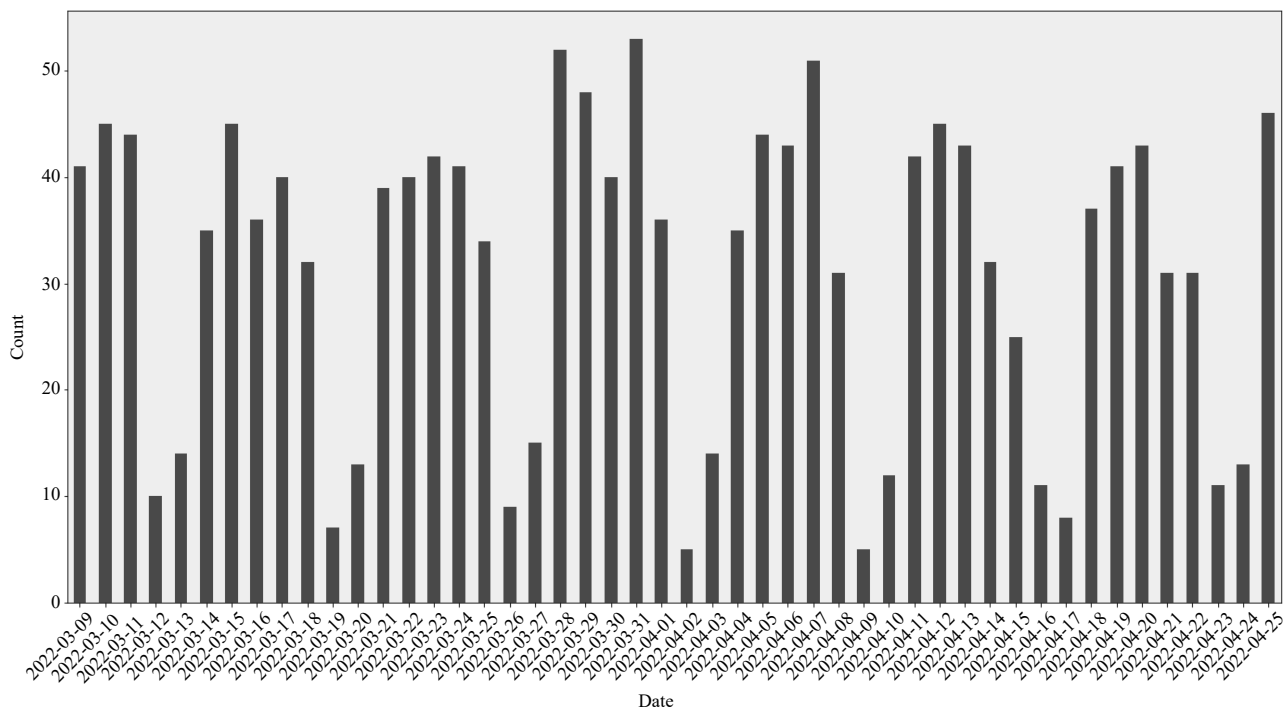


Figure 4. Daily number of collected articles on Forbes' Money News

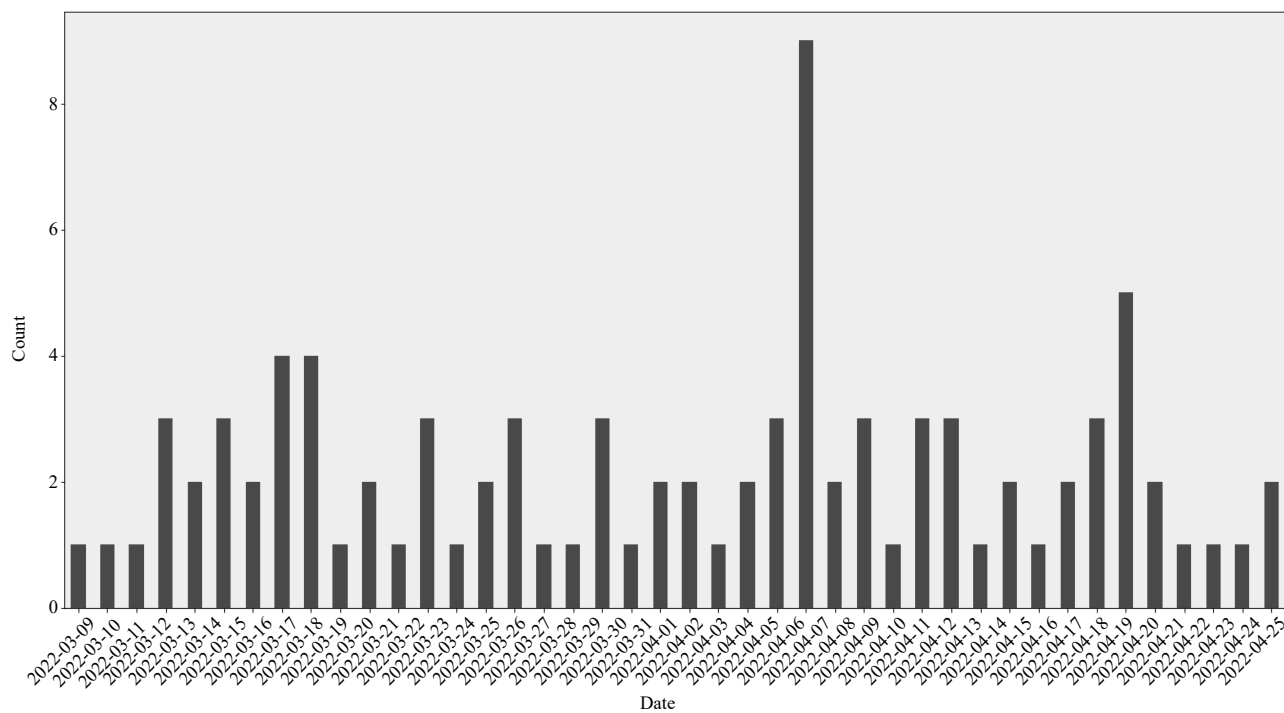
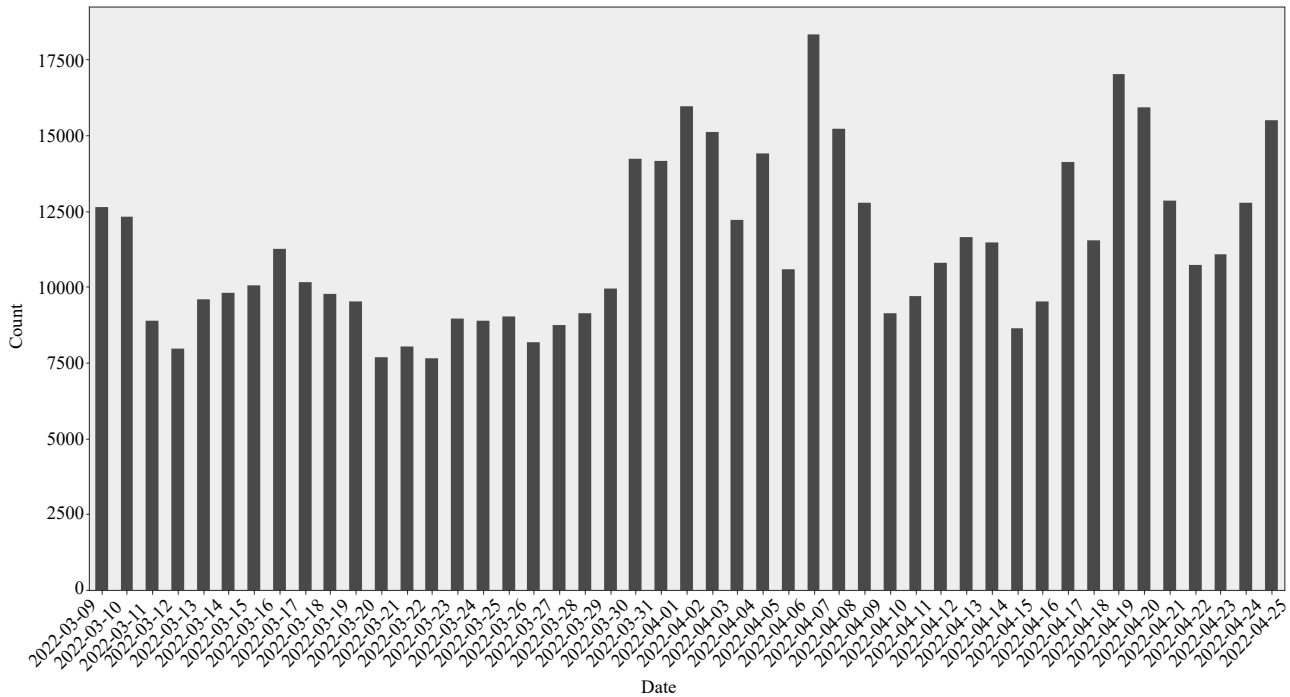


Figure 5. Daily number of collected announcements made by StepN



**Figure 6.** Daily number of collected general discussion from StepN's community group

Data on the prices of cryptocurrencies, including GST and GMT, was obtained through application programming interface (API) calls to CoinMarketCap and Yahoo Finance. Data collection for this study was exclusive to the period between 9 Mar 2022 and 25 Apr 2022. The data was then analyzed using sentiment analysis to construct a daily price chart and a predictive model for forecasting pricing trends. Table 2 provided the top five samples that Yahoo Finance extracted, which include several variables: date, open, high, low, close, adj close, and volume. The “adj close” is associated with sentiment score later to be used in the prediction model to evaluate the performance of the sentiment result.

**Table 2.** Sample data extracted from Yahoo Finance

Date	Open	High	Low	Close	Adj close	Volume
March 31, 2022	2.03	2.63	1.80	2.49	2.49	4,354,715,637
March 30, 2022	1.69	2.29	1.63	2.03	2.03	4,046,877,890
March 29, 2022	1.13	1.85	1.03	1.69	1.69	3,416,864,700
March 28, 2022	0.77	1.14	0.77	1.14	1.14	1,707,162,473
March 27 2022	0.76	0.79	0.74	0.77	0.77	28,680,283

### 3.3 Machine learning models

In our research, we chose FinBERT to generate sentiment scores and utilized XGBoost as the prediction model. The sentiment results obtained from FinBERT classified the statements into positive, neutral, or negative polarity, and we applied these results to the prediction model to assess whether they improved the overall prediction accuracy.



### 3.3.1 FinBERT

FinBERT is a specialized NLP model that is pre-trained to analyze the sentiment of financial text [13, 16]. It is built by adapting the BERT language model specifically for the finance domain, using a vast corpus of financial data to fine-tune it for financial sentiment classification. This process involves training the model to understand the nuances of financial language and terminology, allowing it to accurately detect positive, negative, and neutral sentiment in financial news, reports, and other documents. Because of its focus on the financial domain, FinBERT is well-suited for sentiment analysis in finance-related applications.

### 3.3.2 XGBoost

XGBoost is a powerful and widely used machine learning library that utilizes various concepts and algorithms from the fields of supervised machine learning, decision trees, ensemble learning, and gradient boosting. In supervised machine learning, we train a model using labeled data, where each data point is associated with a label or outcome variable [17]. Decision trees are a type of machine learning algorithm that builds a tree-like model for making decisions by recursively splitting the data based on different features. Ensemble learning involves combining multiple models to improve overall prediction accuracy. Gradient boosting is a popular ensemble learning method that combines multiple weak models to create a strong model that can make accurate predictions on complex datasets.

XGBoost takes these concepts and algorithms and applies them to create a scalable and efficient gradient-boosted decision tree model. It works by iteratively adding decision trees to the model and adjusting the weights of misclassified data points to improve prediction accuracy. The library also provides a range of features such as cross-validation, regularization, and parallel processing, making it a popular choice for a variety of machine learning problems such as regression, classification, and ranking.

## 3.4 Evaluation indicator

FinBERT is a pre-trained NLP model that can be used to generate sentiment scores for text in the financial and investment domains. While the original researchers of FinBERT evaluated the model's accuracy using metrics such as accuracy, cross-entropy loss, and macro F1 average [13, 16], this research focused on evaluating the effectiveness of incorporating the sentiment scores generated by FinBERT into a predictive model (XGBoost) for forecasting the prices of StepN's GST and GMT tokens. The comparison was made by measuring the mean absolute error (MAE) of the XGBoost model with and without sentiment scores as independent variables.

### 3.4.1 Classification labels definition and evaluation indicator for FinBERT

Although this is a pre-trained model, the prediction value of how it is evaluated is defined as follows:

#### 3.4.1.1 Accuracy

In this classification, accuracy means True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Table 3 is the confusion matrix that how it measures the definition:

Table 3. Confusion matrix

		Predicted value	
		Positive	Negative
Actual value	True	TP	TN
	False	FP	FN

Equation:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

### 3.4.1.2 Cross-entropy loss

The cross-entropy loss function, also known as log loss or logistic loss, is a commonly used loss function in machine learning. It is used to calculate the difference between the predicted output and the actual output in a classification problem.

The cross-entropy loss function calculates a score or loss for each predicted class probability based on how far it is from the actual expected value of 0 or 1. The penalty for this score is logarithmic in nature, which means it yields a large score for large differences close to 1 and a small score for small differences tending to 0.

During model training, the goal is to minimize the cross-entropy loss. This is achieved by adjusting the model weights until the loss is as small as possible. A perfect model would have a cross-entropy loss of 0.

Cross-entropy equation is defined as:

$$L_{CE} = -\sum_{i=1}^n t_i \log(p_i)$$

where  $t_i$  is the truth label  
 $p_i$  is the probability for the  $i^{\text{th}}$  class

### 3.4.1.3 Macro F1 average

The F1 score is a metric used to evaluate the performance of a classification model, and it is calculated based on precision and recall. It is commonly used for binary classification problems but can also be applied to multi-class problems.

When dealing with multi-class classification problems, the F1 score can be calculated for each class separately and then aggregated in some way to obtain an overall F1 score for the dataset. One way to aggregate the F1 scores is to use the macro F1 score, which simply takes the average of the F1 scores for each class.

It's important to consider the appropriate aggregation method based on the problem at hand, as different methods may be more appropriate depending on the class distribution in the dataset.

Macro F1 average required precision and recall metric, which are defined as follows:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$
$$\text{recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$
$$\text{F1} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$
$$\text{Macro F1 score} = \frac{\text{Sum(F1)}}{\text{Number of classes}}$$

where number of classes for this research is three (positive, neutral, and negative).

### 3.4.2 Regression prediction evaluation indicator for XGBoost

The main evaluation indicator used to measure the performance of the prediction model XGBoost is the MAE. The MAE is used to determine whether the inclusion of sentiment scores improves the overall accuracy of the model. As such, the focus is on measuring the difference between the actual values and the predicted values generated by

XGBoost, with a lower MAE indicating better performance. By only using MAE as the evaluation metric, it is a clear and concise measure of the model's accuracy and allows a direct comparison between the performance of XGBoost with and without sentiment scores.

MAE equation:

$$\frac{|y_i - y_p|}{n}$$

where  $y_i$  = actual value;  $y_p$  = predicted value;  $n$  = number of observations/rows.

## 4. Experimental results and discussion

### 4.1 FinBERT - Sentiment results

In a previous experiment using FinBERT and the Financial PhraseBank dataset, the accuracy rate was found to be 86% and the F1 score was 84%. The AI investment framework depicted in Figure 3 involves several crucial steps, including the preprocessing of textual data to eliminate stopwords, punctuation, and special characters. Additionally, the text is lowercased, negation is handled, and stemming is performed using regular expressions and the Natural Language Toolkit (NLTK) [18]. These steps are essential to ensuring that the text data is clean, standardized, and ready for analysis. The preprocessed text data can greatly improve the accuracy and effectiveness of NLP models, allowing for more accurate sentiment analysis and ultimately more informed investment decisions. NLTK is a popular Python library for creating programs that work with human language data. Furthermore, tokenizing all sentences using NLTK is the process of breaking a large amount of text into smaller units called tokens, and it is crucial in converting text into numeric data for the NLP model (FinBERT). The sentiment score generated by the FinBERT model is based on the input news data. Each sentence in the input is processed through FinBERT, which generates a classification indicating whether the sentiment is positive, negative, or neutral, along with the corresponding probability (logits). The following statement is from the preprocessed data as an example of how sentiment scores are generated:

*“animoca leads million funding round hong kong nft platform amid crypto craze ucollex latest funding round comes sales digital collectibles gaining ground city seen increasing number projects launched past year.”*

	sentence	logit	prediction	sentiment_score
0	animoca leads million funding round hong kong ...	[0.9674181, 0.0042448044, 0.028337164]	positive	0.963173

Example of equation:

$$\text{Sentiment score} = \text{Logit}_1 - \text{Logit}_2$$

Based on the equation above, the example for this case are as follows:

$$\text{Sentiment score} = 0.9674 - 0.0042$$

$$\text{Sentiment score} = 0.9632$$

Therefore, the above sentence is predicted by the FinBERT model to have a positive value of 0.9632, indicating the sentiment associated with it.

To further illustrate the use of multiple sentences within a paragraph, consider the following example. In a paragraph, the statements may have different sentiment meanings. By averaging these sentiments, we can obtain a more favorable sentiment result.

*“With crypto tax evasion growing around the world, a key global body is looking to standardize reporting requirements. However, despite good intentions they could be onerous for the industry to comply with.”*

	sentence	logit	prediction	sentiment_score
0	crypto tax evasion growing around world key gl...	[0.2166585, 0.0037592866, 0.7795822]	neutral	0.212899
1	however despite good intentions could onerous ...	[0.690478, 0.016513273, 0.29300866]	positive	0.673965

Based on the above outcome, the sentiment score’s neutral value is 0.2128, and its positive value is 0.6739, resulting in an average sentiment score of 0.44, which is consistent with the paragraph discussed earlier.

Figure 7 illustrates the daily correlation between sentiment and GST price changes. While there is no correlation for general discussion, others have a correlated pattern. To make the comparison, we use price change to determine if the price is positive or negative for the next day, which enables us to detect a similar direction indication for the sentiment score. For example, suppose today’s GST price is USD 6, and tomorrow’s price is USD 6.60, a 10% increase, and the sentiment score is 0.4, then this is a parallel move.

Furthermore, the sentiment score of both crypto and stock market news could potentially reach 0.4, which is considered a strong correlation, particularly those that hit 0.6 and above. Additionally, StepN’s announcement may potentially hit a sentiment score of 0.15, which aligns with the price change. When examining the crypto and stock market news, some signals provide positive sentiments before the price moves up. This is one of the indicators that is useful for investors to react before the price goes up or sell when negative sentiment is detected.

The relationship between daily sentiment and GMT price change is depicted in Figure 8. While there is not much correlation observed for general discussions similar to GST, there may be some correlated patterns for other cases.

To strengthen the relationship between GST price changes and other sentiments, Figure 9 supplies additional evidence. It reveals that sentiment in the stock market, finance news, and announcements are correlated with price changes, with values of 0.18, 0.11, and 0.18, respectively. Conversely, the correlation between GST price changes and sentiment in crypto news and general discussions is weak, with negative values of -0.017 and -0.02, respectively.

In Figure 10, it is observed that there is a negative correlation between crypto news sentiment and GMT price change. On the other hand, other sentiments have a positive correlation, particularly stock market news sentiment, which has the highest correlation value of 0.21. Interestingly, general sentiment has a positive correlation of 0.16 with price change for GMT, despite the fact that Figure 8’s chart pattern for general discussion does not demonstrate an identical pattern. Thus, the correlation for this prediction may not be as expected.

During the experiments, we noticed that the sentiment score for the GST price change appeared hours or days before the price moved in the same direction, which is valuable information for investors. Figure 11 shows that we can identify good signals for investors to follow. Almost all of them run in parallel compared to the GST price change, providing early signals. For example, in the crypto and stock market news chart in Figure 11, the highlighted green rectangle shows an example of a sentiment score polarity that reacts before the price change. Such signals are potentially useful for investors to react early and apply their strategies to sell or buy for the next move.

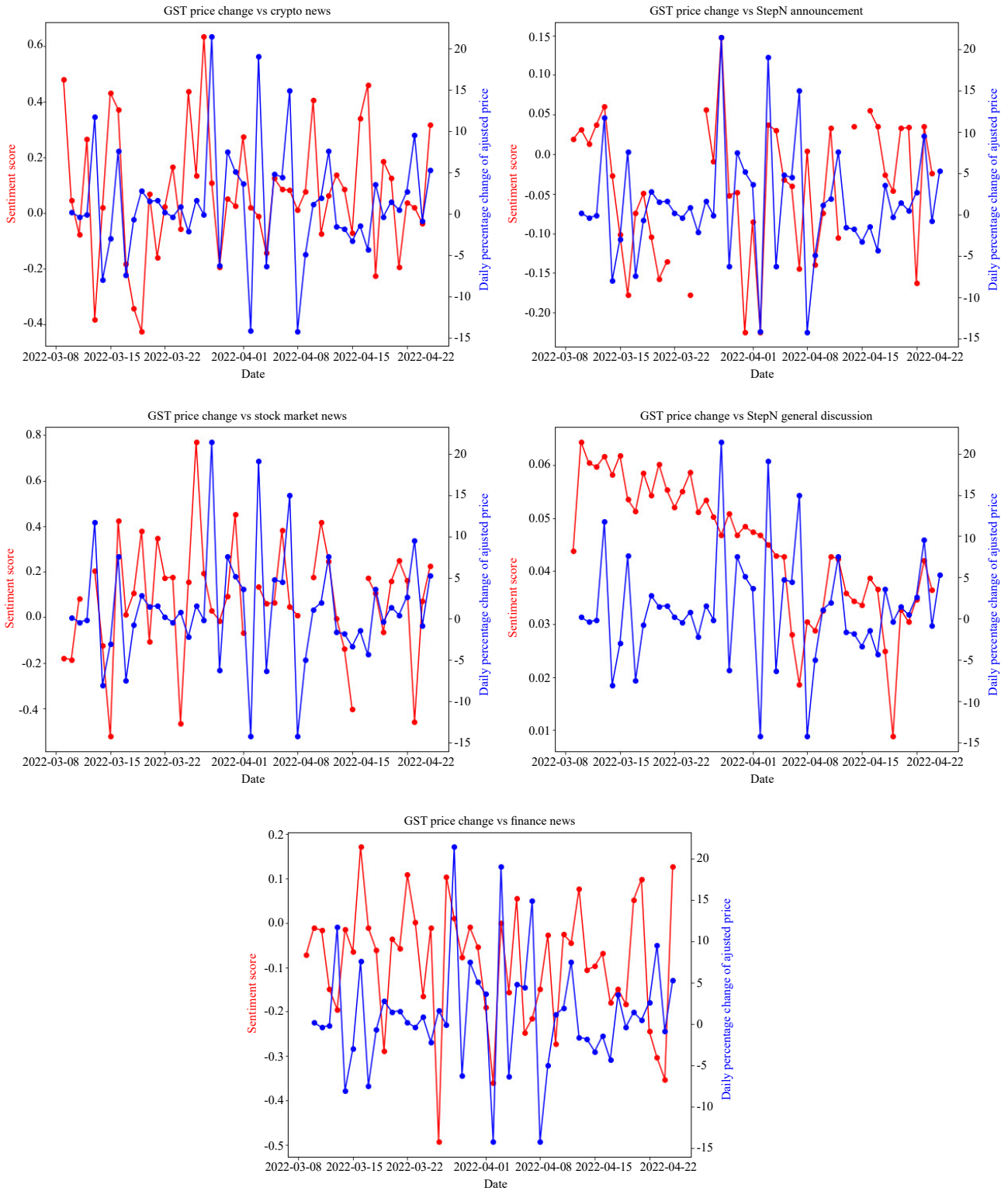


Figure 7. Daily correlations of sentiments between the GST's price change

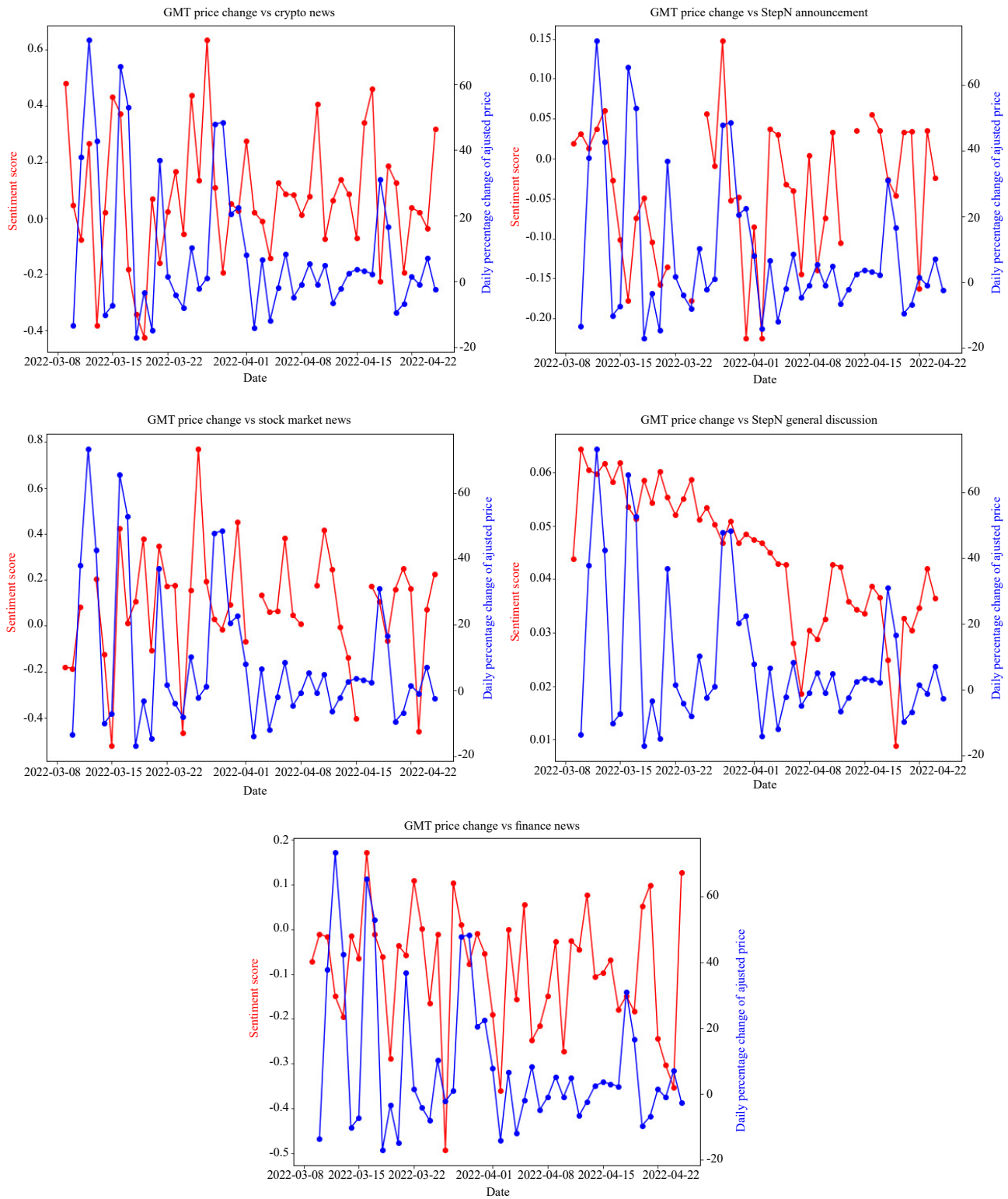


Figure 8. Daily correlations of sentiments between the GMT’s price change

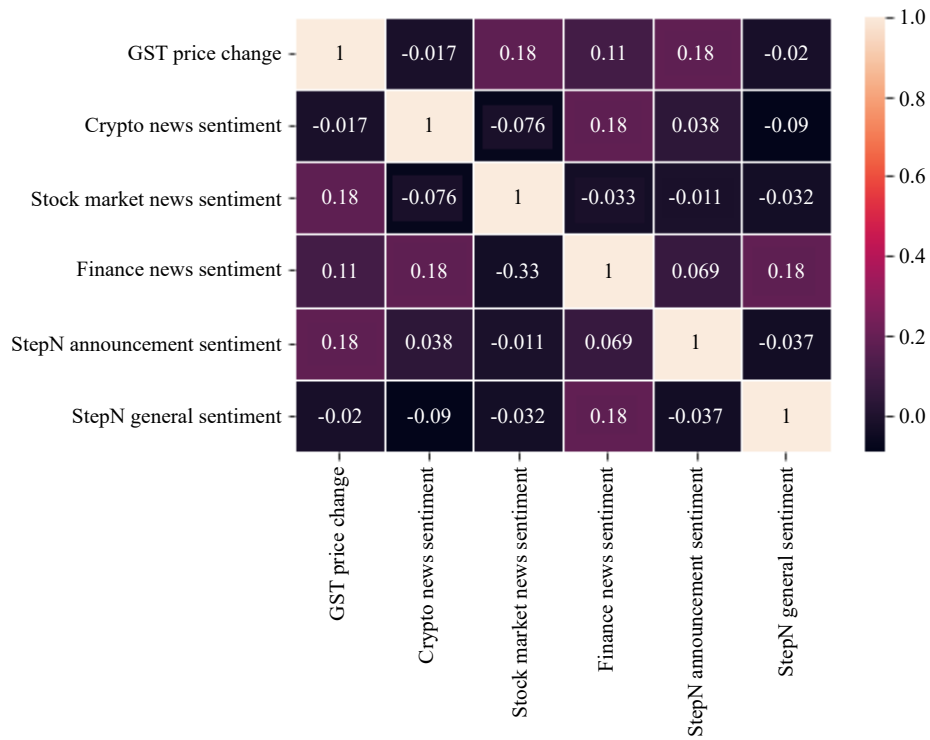


Figure 9. Correlation comparison for GST price with other sentiments

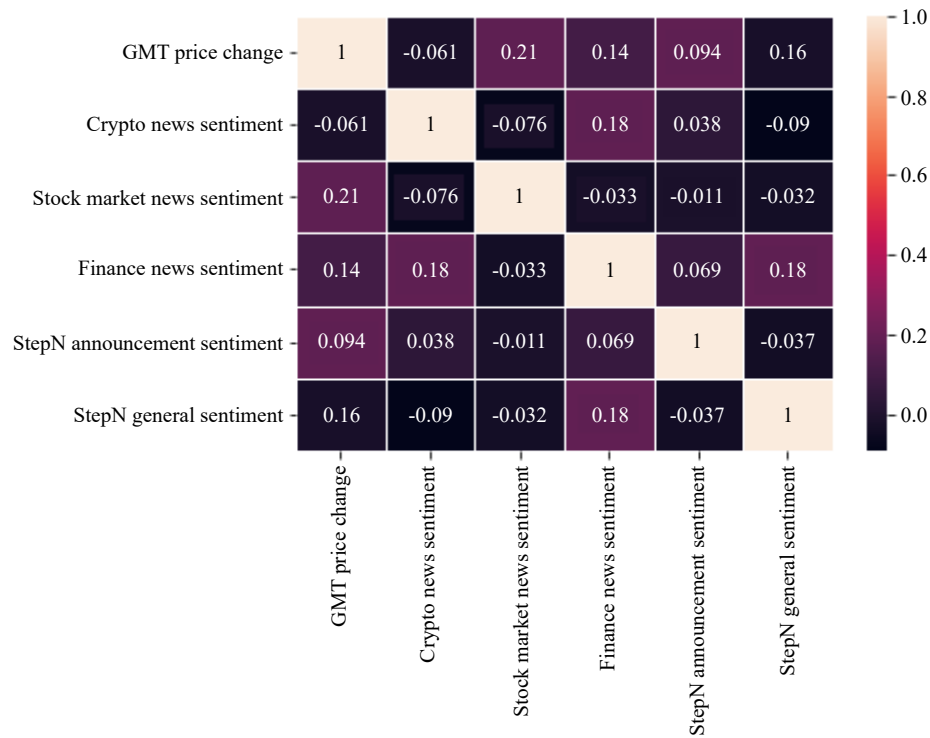


Figure 10. Correlation comparison for GMT price with other sentiments



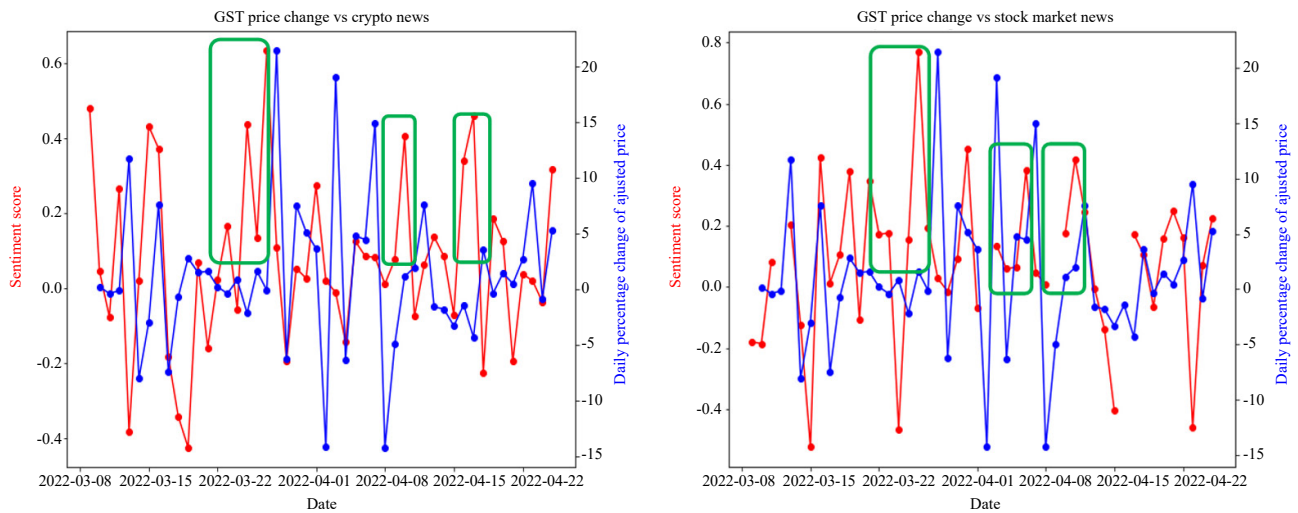


Figure 11. Pattern detected for early indicator to make decision

Table 4 displays a sample dataset with sentiment scores for market events related to cryptocurrencies. One instance is on March 9, 2022, when the US President, Joe Biden, released optimistic news regarding cryptocurrencies, resulting in an increase in GST and GMT prices. Similarly, on March 15, 2022, the sentiment score was 0.92, influenced positively by the news that Binance was granted a legal license to operate an exchange in Bahrain. This news had a favorable impact on the price movement.

Table 4. Crypto news content and sentiment score

Date	Category	Content	Sentiment score
2022-03-09	Cryptocurrencies	Crypto exchange kraken use russian fee...	0.332631
2022-03-09	Cryptocurrencies	Next bitcoin prices latest gains bitcoin price...	0.535309
2022-03-09	Cryptocurrencies	Leak reveals biden crypto plans sending price...	0.551113
2022-03-09	Cryptocurrencies	Biden crypto executive order puts urgency digi...	0.902484
2022-03-09	Cryptocurrencies	Circle crypto future global money crypto poise	0.072739
2022-03-15	Cryptocurrencies	Apple cofounder reveals huge bitcoin price pre...	0.627680
2022-03-15	Cryptocurrencies	Ukrainian crypto rainmaker testify senate hear...	0.018839
2022-03-15	Cryptocurrencies	Amid new executive order white house director...	0.016167
2022-03-15	Cryptocurrencies	Ethereum software company consensys double va...	0.577138
2022-03-15	Cryptocurrencies	Binance wins crypto license bahrain amid middl...	0.921109
2022-03-25	Cryptocurrencies	Crypto trading grow 2022 dfmi matures drives e...	0.436632
2022-03-27	Cryptocurrencies	Crypto bonds exciting due diligence always req...	0.000441
2022-03-27	Cryptocurrencies	Big cryptocurrencies hold price support levels	0.944299
2022-03-27	Cryptocurrencies	Bitcoin crypto braced trillion earthquake ethe...	0.958156
2022-04-10	Cryptocurrencies	Pay doge elon musk surprise twitter plan could...	0.756280
2022-04-10	Cryptocurrencies	Metaverse real estate another crazy crypto mar...	0.054359
2022-04-17	Cryptocurrencies	Race trillion crypto price data reveals bitcoi...	0.785036
2022-04-17	Cryptocurrencies	Crypto banking maturing breaking trust act cry...	0.135857



Since our study relied on a pre-trained model to generate sentiment scores, we were unable to directly evaluate the accuracy rate. However, the earlier research reported an accuracy rate of 86% and an F1 score of 84%. To address this limitation, we applied XGBoost to assess the model's performance. In the following sections, we present the results obtained through XGBoost, which will enable us to evaluate the model's performance and figure out its overall effectiveness.

#### 4.2 XGBoost – Prediction results

We have employed XGBoost as our machine learning technique [17] to generate forecast results for GST and GMT pricing trends by incorporating additional dependent variables derived from sentiment scores. To prepare for the machine learning process of generating forecasting results, two separate datasets were created to predict the trend for GST and GMT, respectively. These datasets included adjusted close price, date, and sentiment scores for finance, stock market, and crypto news. Only sentiment scores with a positive correlation of 0.4 or higher and a negative correlation of -0.4 or lower were selected for these experiments. Splitting the dataset into 70% training data and 30% test data is a common approach in machine learning to avoid overfitting and evaluate the performance of the model on unseen data. Vabalas et al. [19] recommend this split for small datasets to ensure that the model has enough data to learn from and that there is enough data to evaluate the model's performance. By using this split, 70% of the data is used to train the XGBoost model, and the remaining 30% is used to test the model. The model is trained on the training data, and its performance is evaluated on the test data. This allows us to assess how well the model generalizes to new data and to estimate its predictive performance on unseen data. After the preparation of the datasets, we ran the XGBoost model to assess the MAE and determine the accuracy of the model with and without sentiment scores, as influenced by Maleki et al. [20]. MAE is a suitable metric to evaluate the performance of the model in this case, as it provides a measure of the average absolute difference between the predicted and actual values. This is useful for assessing the accuracy of the model in predicting price trends. Therefore, using MAE to evaluate the XGBoost model with and without sentiment scores is appropriate as it can determine the outcome. It was expected that the inclusion of sentiment scores would lead to a better MAE result, demonstrating that sentiment scores play a key role in influencing the price trend. The historical data was used to compare the predictive value against the actual value, with the latter being the “adj close” price value from crypto.

The line chart in Figure 12 compares the XGBoost predictions of the “adj price” for GST based on 40 days of historical data. The MAE result without a sentiment score is 0.319, while the MAE with a sentiment score is 0.296. This suggests that the inclusion of sentiment scores improves the model's performance by a value of 0.023 in terms of MAE. Similarly, for GMT, the sentiment score results in an improvement of the prediction model's overall performance with an MAE value improvement of 0.011, as shown in Figure 13. These results indicate that strong positive or negative sentiment has an impact on the price trend movement of StepN's crypto.

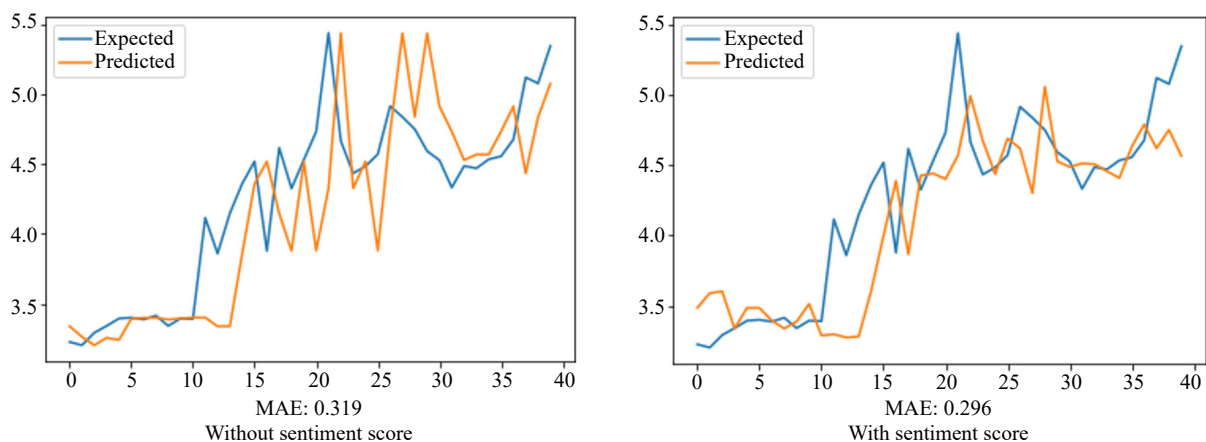


Figure 12. Compare the GST predictive result for MAE value

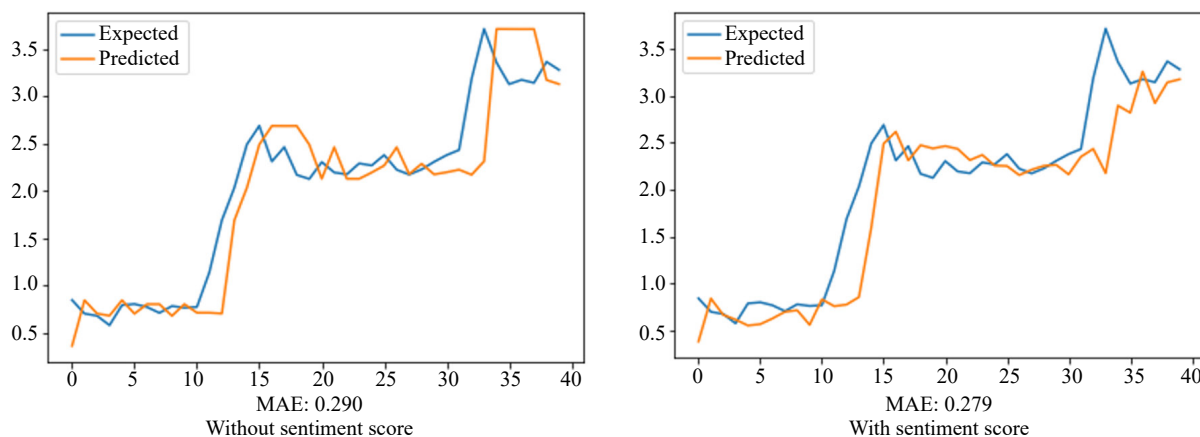


Figure 13. Compare the GMT predictive result for MAE value

The results of the experiment conducted between March 9, 2022 and April 24, 2022 suggest that the positive sentiment score for GST and GMT was highly influenced by financial news. The study also found that there was a strong correlation between the sentiment score and the price change of GST, while GMT had a similar correlation with the price change. This indicates that sentiment analysis can be an effective tool for predicting price changes in the stock market. Furthermore, the experiment helped in determining the MAE result, which is a metric used to measure the performance of prediction models. In addition, the Table 5 scenarios that are used for the prediction algorithms are as follows to improve the MAE:

Table 5. Summary of decision making of buy sell GST and GMT

Criteria	GST	GMT
No news release	Do nothing	Do nothing
Sentiment score is neutral	Do nothing	Do nothing
Crypto, stock market, and finance news sentiment score $\geq 0.4$	Place an order to buy	Place an order to buy
Crypto, stock market and finance news sentiment score $\leq -0.4$ .	Place an order to sell	Place an order to sell
Announcement sentiment score $\geq 0.2$	Place an order to buy	Do nothing
Announcement sentiment score $\leq -0.2$	Place an order to sell	Do nothing
General sentiment score $\geq 0.2$	Do nothing	Place an order to buy
General sentiment score $\leq -0.2$	Do nothing	Place an order to sell

Based on Table 5's summary, the table provides valuable insights into recommended strategies for trading GST and GMT. The table suggests that buying orders should be placed when the sentiment score for crypto, stock market, and finance news is above 0.4 positive sentiment. On the other hand, it is advised to prepare to sell when the sentiment score starts to move towards negative sentiment and to sell when the sentiment is overreacted. Furthermore, if the announcement sentiment score increases to above a 0.2 positive sentiment score, it is recommended to place a buy order for GST. However, if the general sentiment score for GST moves to positive above a 0.2 sentiment score, the recommendation is to hold the position and not trade. These recommendations are based on the strong correlation observed between the sentiment score and the price change for GST. The correlation between sentiment score and price change was found to be stronger for GST than for GMT. Therefore, traders and investors may find these recommendations helpful in making informed decisions about their GST trades.

Overall, sentiment analysis can be a useful tool in developing effective trading strategies, and these

recommendations offer a starting point for incorporating sentiment analysis into investment decision-making. It is important to note that these strategies should not be solely relied upon and should be used in conjunction with other investment strategies and considerations. The market is unpredictable and volatile, and any investment decision should be based on careful analysis and consideration of various factors.

## 5. Conclusion

In conclusion, traditional investment methods such as technical and fundamental analysis and regression models are limited in their ability to detect abnormal situations like the COVID-19 pandemic. To address this limitation, sentiment analysis of news articles can be used to detect trends in the market. However, there is a need for regular updates to machine learning and sentiment analysis models to maintain high accuracy. The study also highlighted the challenge of detecting outstanding crypto, especially in the rapidly evolving DeFi sector. The analysis of different types of textual data and intervals can also produce varying results, and additional news sources could be included to ensure a comprehensive analysis of the impact of news on crypto pricing. For instance, game-related crypto discussions within the community may not necessarily affect crypto pricing, as these discussions may focus only on playing the game more effectively.

Moreover, the analysis of different intervals such as minutes, hours, daily, or monthly can also produce varying results, and obtaining data for minute or hourly intervals may pose a challenge as there are limited sources that provide such granular data, and acquiring access to such data sources can be expensive. In this study, news articles were sourced solely from Forbes, which may have introduced bias into the research. To mitigate this, additional news sources such as CNN, Bloomberg, and others could be included to ensure a comprehensive analysis of the impact of news on crypto pricing.

Despite these limitations, the study provides a novel approach to integrating sentiment analysis and machine learning to predict the pricing of SocialFi and GameFi-linked crypto, such as StepN, and recommends strategies for investors. However, these findings should be interpreted with caution due to the limitations mentioned above. In comparison to other research, this study provides valuable insights into emerging cryptos like GST and GMT and evaluates the pre-trained model using a prediction model. The source code for this study is available at an open source repository ([https://github.com/eikden/StepN\\_Sentiment\\_XGBoost](https://github.com/eikden/StepN_Sentiment_XGBoost)), and future research could overcome the limitations by using alternative data sources, expanding time intervals, and incorporating more advanced sentiment analysis and machine learning models.

## Conflict of interest

There is no conflict of interest in this study.

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