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Research Article

# A Sentiment Analysis of Twitter News Data for Predicting Nikkei 225 Closing Prices

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ABSTRACT

This study investigates the effectiveness of sentiment analysis on Twitter-based news content in enhancing stock market prediction. Tweets from the official accounts of NHK News and Nikkei were analyzed using two sentiment analysis approaches: MeCab combined with the PN Table, and Google Natural Language API (GNL). The final sentiment scores were integrated with Nikkei 225 closing prices to train a predictive model based on Long Short-Term Memory (LSTM) networks. Experimental results indicate that incorporating sentimental features significantly improve forecast performance. While the $R^2$ value of baseline model relied solely on historical stock prices is 0.451, the $R^2$ value of best-performing model incorporating multiple sentiment indicators is 0.705. These findings show that sentimental signals extracted from financial news tweets will play an important role in stock price prediction as valuable inputs.



## 1. Introduction

With the rapid proliferation of social media platforms, researchers have increasingly examined their impact on financial markets. Among these platforms, X (formerly Twitter) stands out due to its scale and real-time nature, making it a particularly valuable data source for analysis. Especially, Bollen et al. [1] conducted sentiment analysis on X using the Profile of Mood States (POMS) psychological index and demonstrated that public mood inferred from tweets could predict the Dow Jones Industrial Average with an accuracy of 0.867 up to three days in advance. This finding underscores the potential connection between social media sentiment and broader societal and economic indicators.

The objective of this study is to analyze tweets posted by the official X (formerly Twitter) accounts of NHK News and Nikkei using two distinct sentiment analysis techniques. By combining the resulting Daily Sentiment Scores with data from the Nikkei 225 stock index, this study aims to predict the index's daily closing prices. The extent to which sentimental data from social media will contribute to forecasting financial market trends is evaluated. Moreover, as a valuable feature of economic prediction models, the potential of sentimental data from social media is assessed in this paper.

## 2. Methodology

### 2.1. *Tweet Collection Using Twitter API*

The Twitter API [2], specifically, the Streaming API which provides real-time access to tweet streams is used for collecting tweet data. This API was configured to collect tweet content, timestamps, and tweet IDs. The data collection process was run every 15 minutes to retrieve tweets from the preceding 15-minute interval, which enabled systematic and continuous data collection. All collected data were stored in a database for subsequent analysis.

### 2.2. *Sentiment Analysis*

Two sentiment analysis approaches, MeCab with the PN Table (MeCab+PN) and Google Natural Language API (GNL), to extract daily sentiment scores for individual tweets have been employed in this paper. Each method assigns a sentiment score on a scale from -1 (negative) to +1 (positive). Then, for each day, the average of all individual tweet sentiment scores was calculated to obtain the Daily Sentiment Score, which was used to construct a time series for forecasting (see Figure 1). In this paper, "sentiment score" refers to the score of a single tweet, while "Daily Sentiment Score" refers to the average score across all tweets posted on a given day.

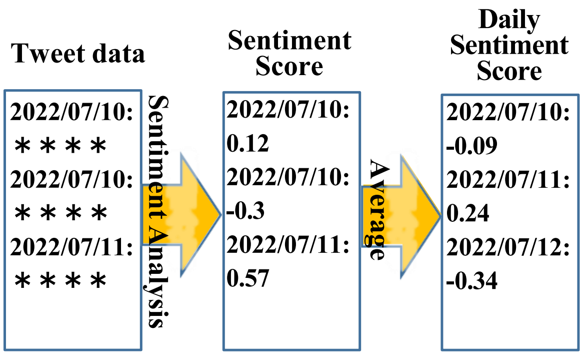


Figure 1 Daily Sentiment Score Computation.

For morphological analysis, tweets were tokenized into individual words using MeCab [3]. Each tweet's sentiment score was then computed by averaging the polarity values of its constituent words, using the PN Table compiled by Takamura et al. [4], which associates words with sentiment polarity values.

Sentiment analysis was also conducted using the Google Natural Language API (GNL) [5], a pre-trained tool for text analysis. This API outputs both a sentiment score for each tweet (ranging from -1 to +1) and a magnitude score indicating the strength of the sentiment. In this study, only the sentiment score was used as the primary evaluation metric, while the magnitude score was disregarded.

### 2.3. *Construction of the Learning Model*

To capture patterns in the Daily Sentiment Score alongside the Nikkei 225 closing prices, a machine learning model based on the Long Short-Term Memory (LSTM) architecture, originally introduced by Hochreiter et al. [6], was developed. Given the differing scales of Daily Sentiment Score and stock prices, min-max normalization was applied to standardize the input values, as shown in Eq. (1):

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

The input features consisted of the Daily Sentiment Scores and Nikkei 225 closing prices from the preceding three days (look-back window), and the model was trained to predict the closing price on the following day. The LSTM model was implemented following the framework proposed by Mhamed et al. [7]. Hyperparameters including the number of units, activation functions (ReLU, Softmax, Tanh), and optimization algorithms (Adam, RMSprop) were systematically tuned. Approximately 100 iterations of tuning were conducted to refine the model architecture and optimize its performance.

### 2.4. *Model Evaluation*

To assess the predictive performance of the constructed model, the dataset was partitioned into training and validation subsets, with 60% of the data allocated to the earlier portion of the time series and the remaining 40% to the later portion. Accordingly, the trained model was evaluated using two primary performance metrics: the coefficient of determination ($R^2$ value) and the root mean squared error (RMSE).

The coefficient of determination, denoted as $R^2$ [8], quantifies the proportion of variance in the dependent variable that can be explained by the independent variables. An $R^2$ value approaching 1.0 indicates a high degree of explanatory power by the model. It is computed using Eq. (2):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(y_{\mathrm{true},i} - y_{\mathrm{pred},i}\right)^2}{\sum_{i=1}^{N}\left(y_{\mathrm{true},i} - \overline{y_{\mathrm{true}}}\right)^2} \quad (2)$$

where $\overline{y_{\mathrm{true}}}$ represents the mean of the actual values.

The Root Mean Squared Error (RMSE) [9] evaluates the average magnitude of the errors between predicted and actual values, with lower values indicating superior predictive accuracy. It is formally defined as Eq. (3):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{\mathrm{true},i} - y_{\mathrm{pred},i}\right)^2} \quad (3)$$

## 3. Sentiment-Based Forecasting of Stock Prices

### 3.1. *Data Collection and Sentiment Analysis*

Between July 10 and December 10, 2022, a total of 22,850 tweets from the official NHK News account (nhk_news) and 3,688 tweets from the official Nikkei account (@nikkei) were retrieved using the Twitter API. Each tweet was archived in a database along with its posting date and textual content. Sentiment analysis was then conducted using two distinct methodologies: MeCab in conjunction with the PN Table (PN), and Google Natural Language API (GNL).

Tweets from the NHK News account analyzed using the PN method are referred to as "NHK_PN," while those analyzed using GNL are denoted as "NHK_GNL." Similarly, sentiment scores for tweets from the Nikkei account were computed using both techniques, resulting in two additional datasets labeled "Nikkei_PN" and "Nikkei_GNL." Together, these four datasets constitute the time series of Daily Sentiment Scores illustrated in Figure 2. The horizontal axis represents the date, and the vertical axis shows normalized sentiment scores ranging from 0 to 1.

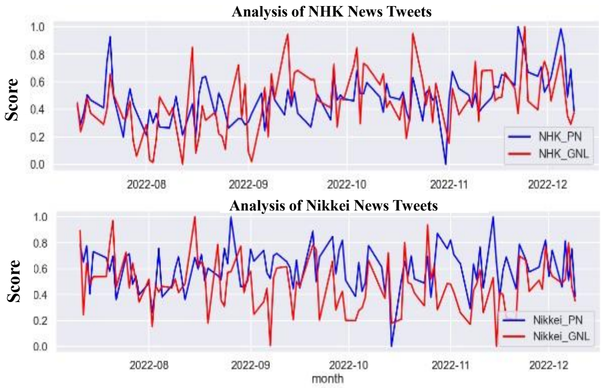


Figure 2 Daily Sentiment Scores of NHK and Nikkei.

Despite normalization, the four sentiment indices shown in Figure 2 exhibit divergent trends and magnitudes. This discrepancy implies that both the sentiment analysis methods and the editorial focuses contribute to differing sentiment interpretations, even when applied to the same time period.

### 3.2. *Correlation and Prediction*

Building on the differences observed in the sentiment trends shown in Figure 2, we conducted a correlation analysis to quantitatively examine the relationships between the sentiment datasets and the Nikkei 225 closing prices.

Table 1 presents the Pearson correlation coefficients between the four sentiment datasets and the Nikkei 225 closing price (denoted as Nikkei_close). The Pearson correlation coefficient ranges from -1 to +1. A coefficient closer to +1 indicates a positive linear relationship, meaning that higher sentiment scores tend to be associated with higher stock prices. Conversely, a coefficient closer to -1 indicates a negative linear relationship, meaning that higher sentiment scores tend to be associated with lower stock prices. Coefficients with an absolute value near 0 (e.g., less than 0.2) suggest little or no linear relationship.

Table 1 Sentiment–Nikkei Correlation Coefficients.

| | Nikkei_close | NHK_PN | NHK_GNL | Nikkei_PN | Nikkei_GNL |
|---|---|---|---|---|---|
| Nikkei_close | 1.000 | 0.024 | -0.049 | 0.002 | 0.191 |
| NHK_PN | 0.024 | 1.000 | 0.398 | 0.088 | 0.028 |
| NHK_GNL | - 0.049 | 0.398 | 1.000 | 0.024 | 0.142 |
| Nikkei_PN | 0.002 | 0.088 | 0.024 | 1.000 | 0.349 |
| Nikkei_GNL | 0.191 | 0.028 | 0.142 | 0.349 | 1.000 |

As shown in Table 1, a weak positive correlation is observed between PN and GNL sentiment scores from the same account. However, correlations between different accounts are nearly nonexistent, likely because the NHK account focuses on general news, while the Nikkei account primarily covers economic topics. The highest correlation with the Nikkei 225 closing price (Nikkei_close), observed in Nikkei_GNL, was still only 0.191. This indicates that sentiment scores alone have limited explanatory power in capturing stock price movements.

To address this, we developed multiple predictive models aimed at forecasting the Nikkei 225 closing price for the following day by using various combinations of sentiment data along with past stock prices. The following indices were assigned to each dataset:

0: Nikkei Stock Average closing price (*Nikkei_close*)

1: NHK_PN

2: NHK_GNL

3: Nikkei_PN

4: Nikkei_GNL

The model names reflect the combination of datasets used. For example, F0 uses only Nikkei_close; F02 combines Nikkei_close and NHK_GNL, and F012 includes Nikkei_close, NHK_PN, and NHK_GNL. Each model was trained on the first 60% of the dataset and validated on the remaining 40%. Model performance was evaluated using the coefficient of determination ($R^2$ value) and root mean squared error (RMSE).

As shown in Table 2, the baseline model (F0), based solely on historical prices, achieved an $R^2$ value of 0.451, indicating limited predictive power. In contrast, incorporating daily sentiment scores alongside Nikkei_close significantly improved model performance. The best results were obtained from model F0124, which integrates sentiment data from NHK_PN, NHK_GNL, and Nikkei_GNL in addition to Nikkei_close, achieving an $R^2$ value of 0.705.

Table 2 Results for $R^2$ Value and RMSE.

| Explanatory variable | $R^2$ Value | RMSE |
|---|---|---|
| F0 | 0.4514 | 0.0143 |
| F01 | 0.5824 | 0.0139 |
| F02 | 0.6110 | 0.0101 |
| F03 | 0.6366 | 0.0095 |
| F04 | 0.6460 | 0.0092 |
| F012 | 0.6374 | 0.0094 |
| F013 | 0.6252 | 0.0098 |
| F014 | 0.6574 | 0.0089 |
| F023 | 0.6370 | 0.0095 |
| F024 | 0.6914 | 0.0080 |
| F034 | 0.6233 | 0.0089 |
| F0123 | 0.6127 | 0.0101 |
| F0124 | 0.7047 | 0.0077 |
| F0134 | 0.6229 | 0.0098 |
| F0234 | 0.6709 | 0.0086 |
| F01234 | 0.5954 | 0.0105 |

[Figure 3](#) and [Figure 4](#) compare the predictive outputs of models F0 and F0124, respectively.

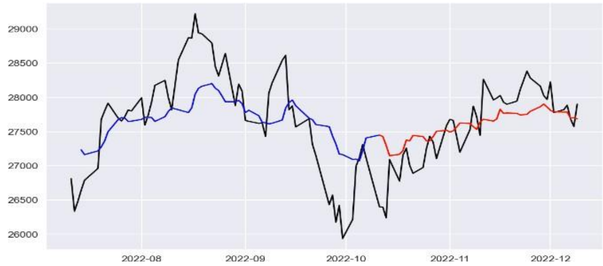


Figure 3 Training and Validation Predictions for F0.

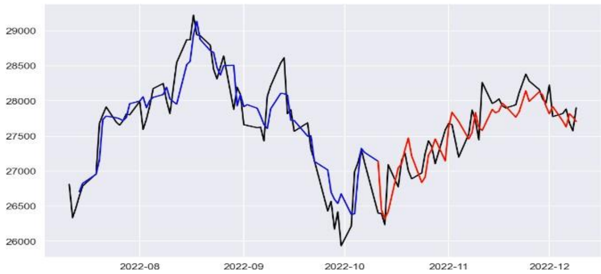


Figure 4 Training and Validation Predictions for F0124.

In each figure, the horizontal axis represents the date, and the vertical axis indicates the Nikkei 225 closing price. The black line shows the actual values, the blue line represents model predictions on the training data, and the red line corresponds to predictions on the validation data.

Model F0, which relies solely on historical prices, fails to capture the fluctuations observed in the actual values, especially during the validation period. In contrast, model F0124, which incorporates multiple sentiment indices, exhibits predictions that more closely follow the actual stock movements, showing improved generalization performance.


Figure 5 Errors associated with the F0 and F0124 models.

Figure 5 illustrates the prediction errors for both models. Each point represents a normalized data pair, with the x-axis denoting the actual closing price and the y-axis indicating the predicted value. Points closer to the diagonal black line (y = x) indicate smaller prediction errors. The F0124 model shows tighter clustering around the y = x line, confirming its improved accuracy. The red box highlights October 12 and 13, 2022, when F0124 significantly outperformed F0. Conversely, the blue box (October 14) marks a case where F0124's performance declined.

One possible explanation for the sharp fluctuations in prediction accuracy around these dates is the Crimean Bridge explosion on October 8, 2022—a major development in the Russo-Ukrainian War. This incident may have influenced NHK's news coverage and affected the sentimental data generated from related tweets, thereby contributing to the observed changes in prediction performance.

These findings demonstrate that incorporating sentiment data from relevant news sources can significantly enhance the predictive accuracy of stock price forecasting models.

## 4. Conclusion

This study demonstrated that incorporating sentiment analysis of tweets from the official Twitter accounts of NHK News and Nikkei will significantly improve the accuracy of machine learning models predicting the Nikkei Stock Average. Sentiment analysis was conducted using both MeCab with the PN Table and Google Natural Language API (GNL). The baseline model F0, which relied solely on past Nikkei closing prices, achieved an $R^2$ value of 45.1%. In contrast, the F0124 model, which integrated sentiment data from both NHK and Nikkei accounts, achieved a substantially higher $R^2$ value of 70.5%, highlighting the predictive value of sentiment information.

However, unlike the findings of Bollen et al., this study did not observe a strong direct correlation between sentiment scores and stock prices. One possible explanation is the nature of the collected tweets, which primarily consisted of news headlines rather than personal opinions or emotionally charged content. In particular, tweets from NHK News often focused on factual reporting of events and tended to contain more neutral or negative tones, limiting the emotional variability that sentiment analysis could capture.

More sophisticated techniques for extracting emotional cues from social media content, especially methods that can better detect subtle sentiment in news-style language could be considered as future tasks. Additionally, longer analysis periods and a wider range of tweet sources could contribute to building more robust and accurate stock price prediction models.

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