

Cognitive Biases and Emotion States Influence Decision-Making in the Stock Market

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Abstract. This research paper is aimed at understanding the role of Cognitive Biases and Emotion states indecision-making in the stock market. This paper uses sentiment analysis and deep learning models to analyze the extent of the effect market sentiment has on predicting stock prices. The study conducts experiments on stock price data and tweet data from the Stocknet database. The Vader model and BERT model were used for tweet sentiment analysis, and this sentiment information was added to the relevant technical indicators and then input into the LSTM model for comparison with the original single LSTM model. The study found that (1) sentiment is information that should be considered in stock price prediction. (2) emotions can influence investors' judgment and further affect stock prices.

Keywords: Psychological Factors, LSTM, Stock Market

1. Introduction

In the area of finance, there is a long-debated topic about whether the price of a stock can be predicted. It is a domain that has driven the focus of many individuals including not only companies but also traders, market participants, and data analysts [1]. In the 1970s, Fama and Eugene proposed the Efficient Market Hypothesis, which became the essential theoretical foundation of modern financial analysis [2]. The hypothesis argues that markets are always efficient and that the prices of securities can efficiently reflect the information available in the market. However, to use this assumption in a real situation, Fama categorized the market into weak, semi-strong, and strong forms according to the degree of effectiveness of the information reflected in the price. However, the theory's premise is so demanding that it is very difficult for the real market to appear in the hypothesis. Henceforth, a large number of econometricians have believed that the use of statistical methods can partly predict the future condition of stocks [3]. With the development of computer technology, machine learning, and deep learning methods have become mainstream ideas in academic research. A large number of researchers have used machine learning to find ways to

effectively predict the stock market. Kumar et al. attempted to compare several traditional machine learning methods to find the one that worked best, which contained Random Forest (RF), Softmax, Naive Bayes, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) [4]. This study found that the algorithms showed different performances for datasets of the same size with Random Forest showing the best performance for large-scale datasets, while Naive Bayes had the best performance in small datasets. With more complex processes and more powerful performance than traditional machine learning, deep learning methods have shown superiority in numerous problems including stock market prediction. Therefore, researchers have widely used this method in the study of stock market prediction problems, such as Artificial Neural Networks (ANN) [5], Recurrent Neural Networks (RNN), Long short-term memory(LSTM) [6], etc. In recent years, hybrid methods have been proven to yield better accuracy and thus have become a popular research trend in the academic community. For instance, Lu et al. proposed a hybrid approach that combines convolutional neural networks, bi-directional long short-term Memory, and attention mechanism to predict the closing price of stock [7]. The method achieved a good performance of R^2 up to 0.9804 in several experiments.

Sentiment analysis has not received enough attention in traditional finance. However, with the emergence and prosperity of the Internet, platforms such as Twitter, stocknet, and other microblogs have brought a vast array of data sources for sentiment analysis in a specific domain including finance. As a result, sentiment analysis in finance has received a great deal of attention over the past 10 years [8]. Financial Sentiment Analysis(FSA), which is an important application in the financial field of psychological sentiment analysis, mainly studies how to extract investor sentiment and emotions from financial texts [9]. Numerous studies have confirmed the existence of a significant impact of investor or market sentiment on financial forecasts [10, 11].

The FSA can source data from corporate disclosures, annual reports, social media, and more. Of these, social media has been the source of much of the research data due to its ability to better reflect the sentiment of individual investors. Previous research has extensively explored the effects of social media on traders' decisions and market outcomes. Bollen et al. investigated the impact of various psychological factors on investor behavior, particularly in the context of the Tehran Stock Exchange in Iran [12]. Their findings indicate that beliefs and self-confidence were found to positively affect investment decisions, whereas emotions such as remorse and regret had a negative impact. Ghelichi et al. analyzed the correlation between collective mood states obtained from extensive Twitter feeds and the Dow Jones Industrial Average (DJIA) [13]. Their study utilized tools to assess mood across six dimensions: calm, alert, sure, vital, kind, and happy.

Currently, there are two main streams of research in FSA, which are techniques and applications [14]. The goal of the technical section is mainly to obtain methods with a higher degree of accuracy. The methodologies currently used in the FSA field can be categorized into four types, the first of which is the Lexicon Approach. The basic idea of the method is to determine the semantic orientation of a document by identifying the semantic orientation of a word. The word semantic orientation needs to be obtained by the constructed dictionary, Harvard IV-4 (HIV4) [15], and Diction [16]. However, using a general-purpose sentiment analysis lexicon in financial text may lead to misclassifying [17]. Yet building a lexicon specialized in the financial domain requires a huge amount of effort and time. The second method is machine learning, Pang et al. first introduced Machine Learning approaches into sentiment analysis [18]. Later on, Zhang et al. discovered the financial value of applying sentiment analysis on a public online stock discussion board, where machine learning techniques are the base of sentiment analysis [19]. Cohen et al. applied Natural Language ToolKit (NLTK) on tweets and was proven to have improved the quality of features

extracted and the performance of the classifier [20]. Alvim et al. investigated the use of Natural Language preprocessing techniques in a way to improve the sentiment classification accuracy of a classical bag of words approach [21]. Sun et al. found that three-class sentiment classification serves as a good tool for doing sentiment analysis on large amounts of online financial texts [22]. Wiegand et al. also pointed out the role of negation in sentiment analysis [23]. The third method is Deep Learning. It can be used to extract incredible information that is buried in huge amounts of textual Data [24]. The most popular algorithms are CNN, LSTM, and Bag-of-Words(BoW). Similar to financial forecasting, the final approach of FSA is a hybrid approach. A model that combines CNN and LSTM has been proposed by Jing et al. [25]. This model achieved a MAPE value of 0.0449, which is better than other conventional models. Talaat et al. propose four deep learning models based on By comparing the model with traditional machine learning methods, the article proves the method as the most effective one [26].

While FSA techniques tend to focus on accuracy, the datasets used generally need to be manually annotated, the applications focus on practicality, and the data used are generally obtained directly from the market. Currently, FSA is mainly applied to causality and correlation testing and financial forecasting. Among them, stock prediction has become a popular research area and NLP methods are widely used [27, 28]. In the task of stock forecasting, the market exists with multiple variables for the researcher to choose from. They can be predicted include stock price, stock price movement, return, volatility, and trading volume [29].

Sentiment analysis has not been emphasized enough in traditional stock forecasting, yet many studies have pointed to the significant impact of sentiment on the stock market. In this paper, we will apply the latest FSA methodology to stock forecasting, combining knowledge from the field of psychology and finance with a view to illustrate and demonstrate how these psychological factors manifest in real-time market behavior.

2. Data

The Stocknet dataset was provided by Xu and Cohen for their research in predicting stock movement [30]. The dataset has two data components from January 2014 through March 2016: a collection of tweets related to the stocks of 87 companies and a historical price dataset of those 88 stocks. We separate the data into two cs sections.

There are a total of 108,589 price data in the price section. The price dataset provides historical stock prices for each company mentioned, including opening, closing, and adjusted closing prices, as well as the highest and lowest prices, and trading volume of each day. These stock price data allow a detailed analysis of how stock prices respond to sentiment news headlines. The details of the data are shown in Table 1

Table 1. Brief description of price dataset

Column	Description	Count
Date	Date of getting data	1258
Name	Stock Company Name	88
Open	Opening price of a stock	108,589
High	Highest price of the day	108,589
Low	The lowest price of the day	108,589
Close	The closing price of a stock	108,589
Adj Close	Closing price after adjustments for all applicable splits and dividend distributions	108,589
Volume	Stock trading volume for the day	108,589

The tweets dataset contains tweets, time, user ID, number of retweets, URL, and many other information. After initial preprocessing, the tweet dataset has a collection of 119844 tweets, each of which is timestamped, and associated with specific stock symbols. The content of the tweets dataset is shown in Table 2.

Table 2. Brief description of tweets dataset

Column	Description	Count
Date	Date of getting data	786
Name	Stock Company Name	87
Text	Content of tweets	119844

3. Methodology

Stock prices are characterized by nonlinearity, discontinuity, and high frequency. This makes it difficult to predict information about stock prices using conventional methods effectively. However, the aforementioned Neural Network is capable of handling such data, which has led to the widespread use of deep learning methods in academia. Meanwhile, NLP has been widely used in the FSA domain, with the emergence of models such as Bidirectional Encoder Representations from Transformers(BERT) [31], Cross-lingual Language Model(XLM) [32], and others. This provides technical support for the research in this paper. The model flow constructed in this paper is shown in Figure 1. Data preprocessing and sentiment analysis are achieved in two ways. First, textual data in the tweets dataset are cleaned using regex. Specifically, URLs, emails, tags, and extra whitespaces are removed. Then, the SentimentIntensityAnalyzer in Vader is implemented to classify data into three sentiment classes. The second way to do this is by implementing Bert for this process, using the “Bert-base-uncased” BertTokenizer. The price data set would be preprocessed separately. Finally, the study will use normalized technical metrics and the sentiment extracted from the tweets to train the LSTM model and evaluate it.

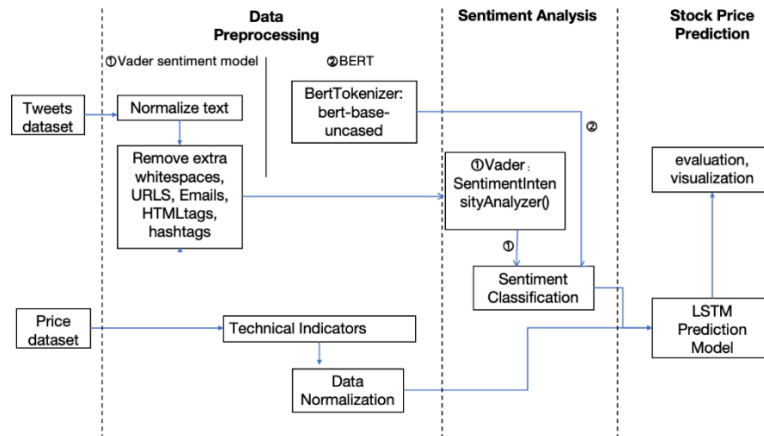


Figure 1. Research flowchart

3.1. Data preprocessing

3.1.1. Tweet section

A. Using BERT

BERT (Bidirectional Encoder Representations from Transformers) is one of the most useful models used for natural language processing (NLP) tasks. In our study, we will mainly use the BERT model to train our tweet dataset. In order to process the data into vectors, the following three steps need to be performed next.

The first is sentence tokenization, namely, the separation of words in a sentence. Tokenized word is a crucial process when applying NLP models because it transforms text into a format that the model can process. The pre-trained BERT model will output logits when passing through the tokenized input text. After all, the Softmax Function will convert logits into probability, which will be used to determine the sentimental score of the texts.

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}} \quad (1)$$

Secondly, we separate the tweet dataset into training and testing datasets. After the dataset is trained, we build a BERT model and fit our dataset into it. Since the model we use requires a “label” column, we assume there is a label with all 0 scores.

Third, we use TensorFlow, which is an open-source machine learning framework developed by Google, to implement and fine-tune our BERT model. As I mentioned previously, the softmax function will return us a probability of mood (negative, positive, and neutral) in each sentence and we use this idea to set up a new “sentimental_score” column. Then, we use the “sentimental_score” column to replace the label column.

In English, the form of the verb will change with the tense of the sentence. To avoid the potential effects of the verb's form on the model, the verb needs to be made prototypical.

After the above steps, the obtained corpus can be effectively used for vectorization and has a minimal impact on the model's performance.

B. Using Vader

The raw tweet dataset contains invalid information such as '@philstockworld', '\$AAPL \$WYNN', '#Samsung', and 'URL'. These meaningless words and punctuations which can interfere with the

model's performance are first removed. VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to the sentiments expressed in social media [33]. It has a great performance on sensing the emotion in tweets data. By using Vader SentimentIntensityAnalyzer, we classified sentiments.

3.1.2. Price section

Technical indicators are often used by professional investors in stock analysis. These indicators are calculated from stock price information and can be used to convey trend, momentum, and volume information about a stock. In addition, these indicators often require the specification of stock price data over some time in the calculation process. For example, the Relative Strength Index(RSI) usually requires data over 14 days, and the Moving Average(MA) is usually calculated using data over five days. Da Costa et al. illustrate that by specifying the time intervals associated with these technical indicators, it is possible to convert them into the vectors required by the model [34]. After selection, the technical indicators chosen for this study are shown in Table 3. The vectors used in this study consist of technical indicators and stock closing prices.

Table 3. Details of technique indicators

Indicator Type	Indicators	Description	Abbreviation
Trend Indicator	Moving Average	The average of stock prices over 5 days	MA(5)
	Moving Average	The average of stock prices over 15 days	MA(15)
	Moving Average	The average of stock prices over 30 days	MA(30)
	Exponential Moving Average	MA that gives more weight to the most recent price over 5 days	EMA(5)
	Exponential Moving Average	MA that gives more weight to the most recent price over 15 days	EMA(15)
	Exponential Moving Average	MA that gives more weight to the most recent price over 30 days	EMA(30)
Momentum Indicator	Moving Average Convergence Divergence	Subtracting the 26-period EMA from the 12-period EMA	MACD(26,12,9)
	Relative Strength Index	RSI measures the speed and magnitude of a security's recent price changes	RSI(14)
	Stochastic Oscillator	Comparing the closing price of the stock to a range of its prices over a certain period	SOSC(14)
	Williams %R	A momentum indicator used to identify potential market reversals and overbought or oversold conditions.	WR(14)
Volume Indicator	On-Balance Volume	An indicator that uses volume flow to predict changes in stock price	OBV(14)

To ensure the speed of convergence and to reflect the size difference between the data, this study will use the normalization method to deal with, the formula as follows:

$$x_{\text{normalized}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (2)$$

Where x is the data to be normalized, $x_{\max}$ is the maximum value of the variable and $x_{\min}$ is the minimum value of the variable.

3.2. Sentiment analysis

As introduced at the beginning of our work, sentimental analysis is a useful tool to detect investors' behavior trends. Incorporating investor sentiment significantly improves stock price prediction accuracy [25]. The text's mood can be detected through sentimental analysis by identifying the emotions in a text as positive or negative. The method we use in this study is similar to what Jing et al. did in their research "A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction".

We utilized the TensorFlow framework from the HuggingFace Transformers library to perform sentiment analysis on the dataset. The process involved several key steps:

1. Preprocess the text: Tokenize the text using BERT's tokenizer.
2. Create a TensorFlow dataset: Convert the tokenized text into a format that TensorFlow can process.
3. Build the model: Use BERT classification to create a model for sentiment classification.
4. Compile and evaluate the model: Train the model on your dataset, then evaluate its performance using appropriate metrics.
5. Set a column with sentimental scores and label all the text with 0, 1, and 2, which represent negative, neutral, or positive mood.

3.3. Stock prediction

To predict stock prices based on the sentimental data, we employed a Long Short-Term Memory(LSTM) neural network model:

1. Construct an LSTM model: Design a multi-layer LSTM model and use cross-validation to avoid overfitting: Since we have 108,589 price data that are not necessarily linear, we try to find models that can compute a large amount of data and also detect implied patterns in the data. Thus, for stock price prediction, we used long short-term memory (LSTM), a kind of RNN. This allows us to trace the long-term stock price fluctuation. By replacing the hidden layers with LSTM cells (each cell contains the following elements in the table), we can improve the accuracy of our prediction [35].

Table 4. Content of a LSTM cell

Cell	Description
Input gate	The input gate consists of the input.
Cell State	Runs through the entire network and can add or remove information with the help of gates.
Forget gate layer	Decide the fraction of the information to be allowed.
Output gate	It consists of the output generated by the LSTM
Sigmoid layer	It generates numbers between zero and one, describing how much of each component should be let through.
Tanh layer	It generates a new vector, which will be added to the state.

2. Evaluation: In this study we used two parameters, Root Mean Squared Error(RMSE) and Mean Absolute Percentage Error (MAPE), to evaluate the results of the model outputs

RMSE indicates the average degree of deviation between the predicted value and the true value. It is calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

Where y_i is real stock price data, $\hat{y}_i$ is the model predicted stock price, and n is the number of data. In general, a smaller RMSE represents a smaller deviation of the predicted value from the true value and a better performance of the model.

MAPE quantifies the prediction error as a percentage and is an important indicator of the accuracy of the predicted value. The advantage of MAPE is that the indicator is sensitive to relative error and does not change due to the global scaling of the target variable. It is calculated as follows:

$$\text{MAPE} = \frac{1}{n} \left| \sum_{i=1}^n \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (4)$$

where y_i is real stock price data, $\hat{y}_i$ is the model predicted stock price, and n is the number of data. The scale of MAPE is $[0, +\infty)$. The closer the MAPE is to 0, the smaller the prediction error is and the better the model performs.

4. Discussion

As mentioned earlier, the data used in this paper contains stock information and tweets from 88 companies. However, tweet data is not available for every company on every trading day. Only large-scale companies such as Apple Inc. and Google Inc. have enough data to support this study for experimentation. Here, the study uses Apple's stock price data for the experiment. In the case of Apple, we obtained stock price data from January 2014 through March 2016 and corresponding tweet data. Out of a total of 565 days of data, tweet data was not obtained for 26 of those days. This experiment sets market sentiment to be neutral for the dates for which no data is available.

4.1. Sentiment analysis experiments

The BERT model used in this paper is a coarse-grained approach. As a result, the BERT model can only output emotional polar. After obtaining the set of sentiments for each tweet, this study will use the most frequently occurring sentiment of the day as the overall sentiment of the market for that day.

The Vader model is a good granularity model. What the model outputs is not a sentiment level but an intensity score. This score can express investor sentiment information at a more granular level. The intensity score ranges from -1 to 1, with closer to 1 indicating a more positive sentiment and, conversely, closer to -1 indicating a more negative sentiment. Similarly, a score closer to 0 means a more neutral view. In this study, the VADER sentiment model in nltk is used to do the recognition of tweet sentiment. After getting the sentiment scores for each day, the study will take the average of each day's score as the intensity score for that day and input it into the model.

4.2. Stock prediction experiments

Some hyperparameters need to be adjusted during the construction of the LSTM model, as shown in Table 5. In the table, the Range column indicates the range chosen for the hyperparameters of this experiment. In constructing the model and tuning the parameters, issues such as computation time, degree of fit, and model convergence need to be taken into account. Layer size and Hidden unit size are related to the complexity of the model. Higher model complexity may result in a better fit, but

can also be very time-consuming. Multiple iterations will cause the model to converge for better fitting performance, but will also introduce overfitting problems as well as being time costly. The batch size can speed up the iteration, but too large a batch size will reduce the accuracy of the model or even cause a misfit phenomenon.

Table 5. Hyperparameter of LSTM details

Hyperparameter	Description	Range
Layers size	the number of LSTM layers in the model	(1,2,3)
Hidden units size	the number of hidden units in a single layer	(100,50,25) (128,64,32)
Epochs size	the number of times that the LSTM passes through the entire training	(0,60)
Batch size	the number of samples that will be propagated through the LSTM	(16,32,64,128)

When Batch size is 64, the losses in this study are shown in Figure 2. It can be seen that when the epoch is 20, the model reaches convergence, and then the training loss will not drop significantly, so the optimal epoch is 20. After several experiments, the model works best when 2 LSTM layers are added to the model with 64, and 128 hidden units in each layer respectively. Fixed learning rates can cause overfitting situations in the later stages of training. Therefore, instead of using a fixed learning rate, this study uses the ADAM optimizer to automatically adjust the learning rate. ADAM adjusts the learning rate of each parameter by calculating the first-order moment estimate and second-order moment estimate of the gradient to achieve more efficient network training.

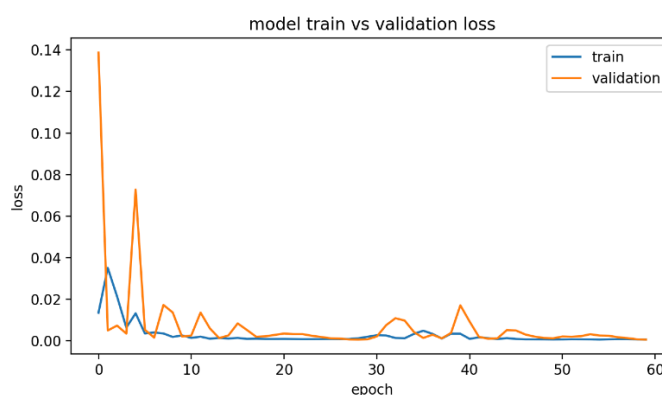


Figure 2. Loss when batch-size=64

4.3. Result comparison

The results of the experimental data for different models are shown in Figures 3-5. The blue line in the figure is the actual stock price and the orange line is the model's prediction. It can be seen that when no sentiment information is added, only the LSTM model can get better results in predicting the stock price, which can roughly reflect the trend of stock price movement. With the addition of the sentiment polar generated by the BERT model, the model shows a better performance, although the trend is still hot with a certain lag, but can be predicted in a refined way. Finally, after adding the sentiment scores output from the Vader model, the model gets the best performance, with some prices even showing some degree of overlap.

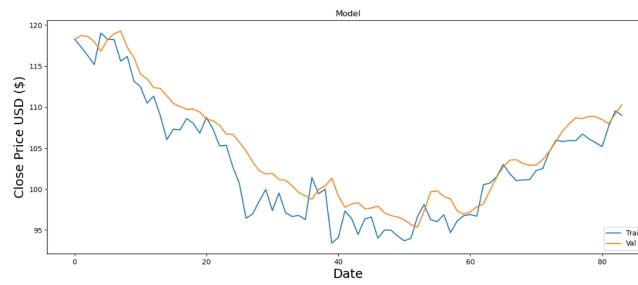


Figure 3. Prediction using only LSTM vs validation

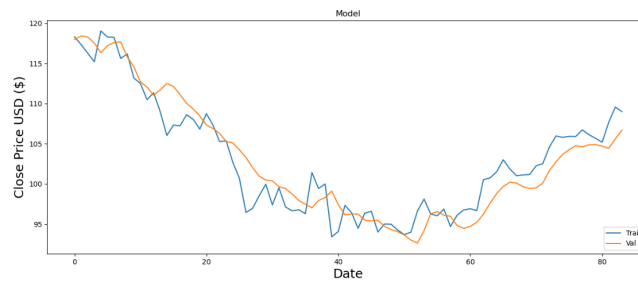


Figure 4. Prediction using BERT and LSTM vs validation

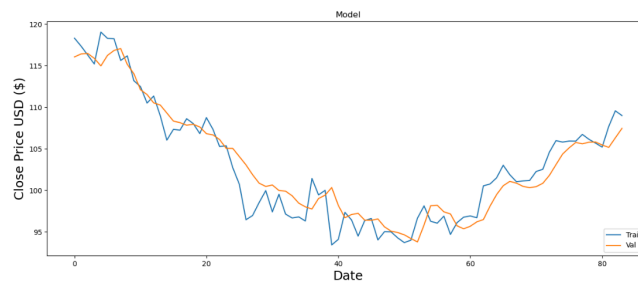


Figure 5. Prediction using vader and LSTM vs validation

Table 6. Accuracy of prediction

	LSTM	BERT+LSTM	Vader+LSTM
RMSE	2.78	2.45	2.14
MAPE	2.20%	1.92%	1.60%

Table 6 shows how the assessment metrics under each of the different models, with RMSE and MAPE showing consistency. Combining the two metrics, the model of Vader+LSTM has the strongest performance in prediction. First, the LSTM model with the input of emotional information possesses better performance than the original model. This suggests that emotions can indeed influence investors' judgment and further affect stock prices. It also shows that sentiment is information that should be considered in stock price prediction. Considering the difference shown in the output of BERT and Vader, the previous conjecture of this study is further validated. Investors sentiment can have an impact on their investment judgment; a single investor may not be able to have a huge impact, but when most of the investors in the market hold the same view and thus

become the market sentiment, such sentiment will have some impact on the stock price. Moreover, the intensity of sentiment can also influence the country.

5. Conclusion

BERT & LSTM produced an RMSE of 2.4503 and MAPE of 1.92%, showing a relatively good prediction performance. VADER & LSTM achieved the best results with an RMSE of 2.1393 and MAPE of 1.60%. Using only LSTM produces the worst result, with RMSE at 2.7759 and MAPE of 2.20%.

The displayed results showed that market sentiment is one of the influencing factors of the stock price, and incorporating sentiment analysis into stock price prediction models improves accuracy. Because sentiment scores represent Cognitive Biases and Emotion States, and stock prices reflect Decision-Making in the Stock Market. We can conclude that Cognitive Biases and Emotion States Influence Decision-Making in the Stock Market.

This research has several limitations. First, it doesn't cover all social media platforms. It is exclusively focused on Twitter posts, excluding sentiment analysis from traditional media sources such as financial newspapers and radio. Second, cultural and demographic variations and information access are limited. Users of Twitter and their posts are selective. Many countries and their citizens are restricted from accessing Twitter. Thus, the data utilized do not represent a comprehensive global perspective. Third, this study only focuses on English texts. Emojis, pictures, and texts in other languages are not identified. Finally, sentiment scores are only classified into three sentiment classes: positive, negative, and neutral. This is not considering the complexity of human emotions, ignoring the intensity and other emotions such as frustration, excitement, or hesitation. These limitations may lead to a less precise market sentiment detected, making our predictions less accurate and less likely to be generalized to a world scope. In future work, efforts could be made to gather a more comprehensive dataset that includes all trading days. Emojis and images could also be analyzed, using an image recognition model, such as a convolutional neural network (CNN). Emotions could also be more accurately identified by using a more advanced fine-grained sentiment analysis algorithm.

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