Social Media Sentiment Analysis For Stock Market

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Abstract

Stock-Sentiment is a deep learning model that uses natural language processing to analyze Twitter(X) data and predict the stock market trends. This model aims to summarize financial related tweets and analyze historical stock price data. The system involve several machine learning and deep learning techniques, including FinancialBERT, RandomForestClassifier to predict the stock price movements. Our system aims to fine tune the transformer-based model to analyze the social sentiment and then predict the stock market trend by using RandomForest classifier.

Assentation of Teamwork

- **All:** Presentation & Report
- **Litao (John) Zhou**
  - Implemented the pre-processing mechanism for Twitter data.
  - Fine-tuned the FinancialBERT and RandomForestClassifier models.
- **Yuhan Zeng**
  - Collected datasets for financial-news tweets and Tesla-related tweets.
  - Established the FinancialBERT and RandomForestClassifier models.
- **Zeying Zhou**
  - Collected datasets for financial-news tweets and Tesla-related tweets.
  - Fine-tuned the FinancialBERT and RandomForestClassifier models.

1 Introduction

Nowaday, people often post different information together with personal emotions and feedback on various social media. Sentiment analysis is a Natural Language processing technique that analyzes the text's emotion tone, attitudes or opinions. Conducting sentiment analysis on social media can reveal public opinion trends, market sentiment shifts, and emerging narratives that influence consumer behavior, stock prices, and economic trends. Thus, analyzing investment-related social media sentiments can provide valuable insights into stock price trends and movements. Our project aims to establish a deep learning model that predicts stock price movements by analyzing sentiment of Twitter(X) posts using a transformer-based NLP neural network. By deploying our model, we could predict the future stock market based on social media statistics.

2 Preliminaries and Problem Formulation

For our project, our goal is to develop an NLP(Natural Language Processing) deep learning model that processes financial textual input and classifies sentiment related to financial stock movements

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based on Twitter(X) data. We intend to determine how sentiment analysis of posts can contribute to stock trend prediction. Firstly, we would establish the model that predicts the sentiment based on the financial-related Twitter.

- **Input:** "The new product launch by Company X is receiving massive positive attention. Many analysts are bullish!"
  Output: Bullish (Positive Sentiment, Potential Price Increase)
- **Input:** "Market looks really uncertain today. Too much volatility, I'd stay away from tech stocks."
  Output: Bearish (Negative Sentiment, Possible Price Drop)
- **Input:** "Earnings report is out. Mixed reactions, but no significant movement in after-hours trading."
  Output: Neutral (Stable Market Condition)

Then, given historical stock price data and Twitter sentiment, we would manually define a label based on a defined time window:

- **Price Increase:** if today's closing price $>$ yesterday's
- **Price Decrease or No Change:** if today's closing price $\leq$ yesterday's

Our ultimate goal is to predict stock movement direction using sentiment and historical price trends.

3 Solution via Deep Learning

Our solution includes two parts. The first part involves deploying a pre-trained model (FinancialBERT(1)) to classify the sentiment of tweets, and the second part predicts the stock price based on the sentiment analysis results from part 1.

3.1 Sentiment Analysis

For the dataset, we use "zeroshot/Twitter-financial-news-sentiment" zeroshot (2), which is "an English-language dataset containing an annotated corpus of finance-related tweets". And it is used to classify finance-related tweets for their sentiment in this project. We select the pre-trained model, FinancialBERT, to classify the dataset. It is a transformer based model which outperforms traditional BERT because of its ability on dealing with financial-related text.

The sentiment analysis process starts from classifying financial tweets into bullish, bearish, or neutral categories using FinancialBERT. Since traditional sentiment analysis models often fail to capture the nuances of finance-related discussions on Twitter, we could fine-tune FinancialBERT on a dataset specifically dealing with financial Twitter to improve classification accuracy. We pre-process the Twitter posts by removing URLs, hashtags, and repeate punctuation etc while preserving key financial terms. Each processed tweet is vectorized and passed through the fine-tuned FinancialBERT. Its self-attention mechanisms could analyze contextual relationships between words to determine sentiment. The model assigns a probability score to each sentiment class, and the final classification is obtained by selecting the category with the highest probability among the three labels.

3.2 Price Prediction

In this part we leverage sentiment analysis outputs to forecast stock price movements. For predicting the price movement, we could use the "RandomForestClassifier" model to achieve the goal.

In the updated prediction model, we incorporate both sentiment analysis outputs and historical stock price data to forecast daily stock movements. After performing sentiment classification on tweets using a fine-tuned FinancialBERT model, we combine the sentiment labels with real-world stock data from 2022, specifically using adjusted closing prices (3) for the TSLA stock. The sentiment labels are encoded into numerical values (e.g., Bullish = 1, Neutral = 0, Bearish = -1) to be used as machine learning features. These sentiment signals are then merged with stock data based on corresponding dates to form a unified dataset.

From each day of this combined dataset, we aggregate the sentiment scores and adjusted closing prices of the past two weeks. These features help the model capture short-term sentiment trends and price momentum. The target variable is a binary label indicating whether the adjusted closing price of the following day increased compared to the current day. This framing transforms the task into a binary classification problem.

We employ a RandomForestClassifier to learn patterns in the data. This ensemble method benefits from multiple decision trees to reduce overfitting and improve prediction accuracy. The model is trained on a training set and evaluated using accuracy metrics on a separate test set. The experimental results demonstrate the potential of combining financial sentiment from social media with market data to enhance stock trend prediction. This hybrid approach provides a practical, interpretable framework for leveraging public sentiment in financial forecasting.

4 Implementation

Our project aims to analyze Twitter sentiments and stock market are related and investigate its effect on Tesla's stock price using deep learning models.

Dataset

- $\sim$12,000 financial-news tweets manually labeled as bearish, bullish, or neutral (three labels equally separated).
- $\sim$37,000 Tesla-related tweets and Tesla stock price from 2021.09.30 to 2022.09.30.

Preprocessing Stage

We use a Twitter-cleaning mechanism based on regular expressions (regex) to remove noise such as URLs, hashtags, tickers, emojis, and punctuation. This is applied to both labeled financial-news tweets and Tesla-related tweets.

Model Training

We tokenize the labeled financial-news tweets and apply them to fine-tune a **FinancialBERT** model.

Sentiment Prediction for Tesla-related tweets

We apply our fine-tuned FinancialBERT model to predict sentiment scores (bullish/bearish/neutral) for the Tesla-related tweets. The output is a cleaned dataset labeled with sentiment.

Stock Prediction

We use a **Random Forest** classifier to model the relationship between sentiment and Tesla stock prices (2021.09.30–2022.09.30). Input features include the daily average sentiments and the closing price as well as the end of the day before.

5 Numerical Experiments

To evaluate the proposed sentiment-informed stock prediction pipeline, we conducted a series of numerical experiments covering both the sentiment classification and price movement forecasting tasks. These experiments involved training and evaluating a fine-tuned transformer model on finance-specific sentiment data and using its outputs in a traditional machine learning model for predicting next-day stock direction.

5.1 Sentiment Classification via FinancialBERT

We fine-tuned the FinancialBERT model on a financial Twitter dataset consisting of 300 labeled tweets across three sentiment classes: Bearish, Neutral, and Bullish. The model was trained for 2 epochs using a learning rate of 2e-5, batch size of 16, and weight decay of 0.01. The final evaluation

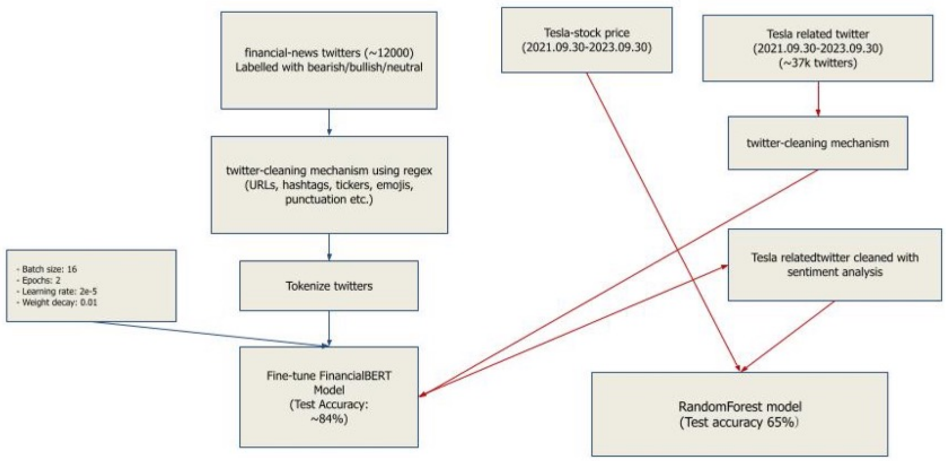

Figure 1: Implementation

yielded an accuracy of 83.66% and a weighted F1-score of 0.83 shown in the following figure, suggesting strong generalization on unseen data.

Epoch	Training Loss	Validation Loss	Accuracy	F1
1	No log	0.380533	0.836667	0.830945
2	No log	0.414094	0.826667	0.824852

Figure 2: Finetuned FinBERT Loss & Accuracy

A detailed classification report showed F1-scores of 0.64 (Bearish), 0.79 (Neutral), and 0.89 (Bullish), with the model performing best on the Bullish class due to its relatively larger support size (n = 194). The confusion matrix revealed that most misclassifications involved confusing Bearish tweets as Bullish shown in the following figure, which can be attributed to subtle or sarcastic expressions in financial discourse. Overall, the fine-tuned FinancialBERT model showed reliable performance in capturing investor sentiment.

	precision	recall	f1-score	support
Bearish	0.75	0.56	0.64	48
Neutral	0.83	0.76	0.79	58
Bullish	0.85	0.93	0.89	194
accuracy			0.84	300
macro avg	0.81	0.75	0.77	300
weighted avg	0.83	0.84	0.83	300

Figure 3: Classification Report of Finetuned FinBERT

5.2 Stock Price Movement Prediction via Random Forest

Using the output of the sentiment classifier, we computed daily average sentiment scores and merged them with historical TSLA stock data obtained from the dataset in 2022(4). The merged dataset

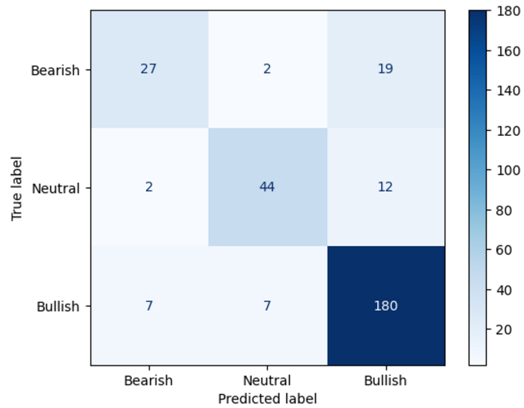

Figure 4: Confusion Matrix of Finetuned FinBERT

included technical features such as Open, High, Low, Close, Adjusted Close, Volume, and a binary label indicating the trend of the next day's closing price (1 for increase, 0 otherwise).

We trained a Random Forest classifier using 100 estimators. The model achieved a test accuracy of 65%, with precision and recall scores of 0.72 and 0.68 respectively for upward price predictions. The classification report yielded a macro-average F1-score of 0.64, and the confusion matrix illustrated that while the model performed reasonably well on "Up" days, it occasionally confused them with "No Change/Down" days.

	precision	recall	f1-score	support
Down/No Change	0.55	0.60	0.57	20
Up	0.72	0.68	0.70	31
accuracy			0.65	51
macro avg	0.63	0.64	0.64	51
weighted avg	0.65	0.65	0.65	51

Figure 5: Classification Report of Prediction Model

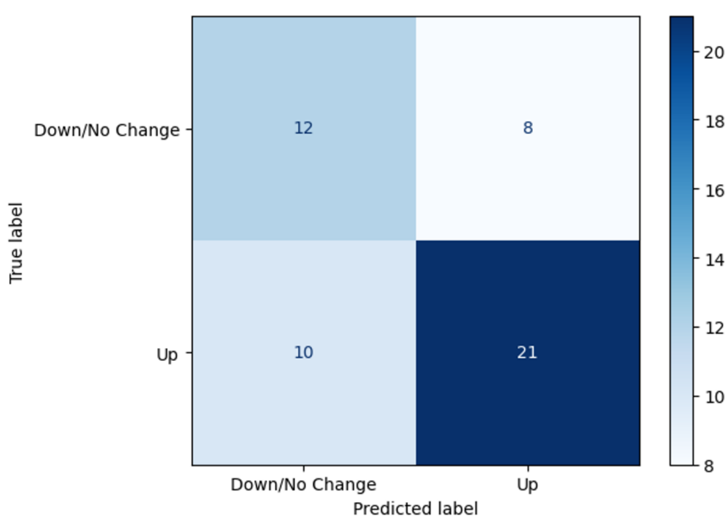

Figure 6: Confusion Matrix of Prediction Model

The ROC curve indicates an AUC score(5) of 0.64 (refer to Appendix. A), suggesting the model has moderate but not strong ability to distinguish between classes (better than random, but with room for improvement).

The correlation matrix (refer to Appendix.B) shows that Volume and Average Sentiment have relatively low linear correlation with the Next Day Trend target variable (0.03 and -0.044 respectively), but compared to traditional price features like Open, High, Low, and Close, which all have similar weak negative correlations (around -0.14 to -0.15), these two features may still offer unique predictive value. Notably, Volume and Average Sentiment are not strongly correlated with other features, indicating they may provide non-redundant, complementary information to the model.

Together, these numerical results validate our model pipeline and demonstrate that integrating financial sentiment with price data enhances the predictability of short-term stock trends.

6 Answer Research Questions

For our design, by fine-tuning FinancialBERT on a sentiment labeled financial-news tweet dataset, we achieved 84% accuracy in sentiment classification. This reveals that transformer-based models are effective at detecting financial sentiment.

When historical stock prices were mixed with sentiment predictions as input features to a Random Forest classifier, we achieved an accuracy in predicting stock movement of 65% for Tesla (TSLA) stock and this could prove that social media sentiment related to future stock market change.The Random Forest Classifier showed generally decent performance of higher accuracy when input sentiment features are integrated with the historical stock price data. This hybrid approach shows that combining both historical price and sentiment data can improve predictive accuracy.

7 Conclusions

Overall, our team successfully developed a model using FinBERT, conducted sentiment analysis on tweets, and reached a final accuracy of 65% for predicting future stock market movements.

Based on our current progress, future improvements for this project include fetching X's API for live sentiment tracking. By getting the metadata, we could combine the sentiment analysis results into a daily weighted sentiment score by factoring in the number of retweets, giving more influence to widely shared tweets. This score, along with historical adjusted closing prices, is used as input features for the prediction model. The model then classifies whether the stock price will rise or not the next day. Performance improves when using a lookback window of historical sentiment and price data, with weighted sentiment showing a clear advantage over unweighted sentiment in predicting daily stock movement. We are confident it can be built as a more reliable and stronger prediction system in the financial field.

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Appendix

- Appendix. A

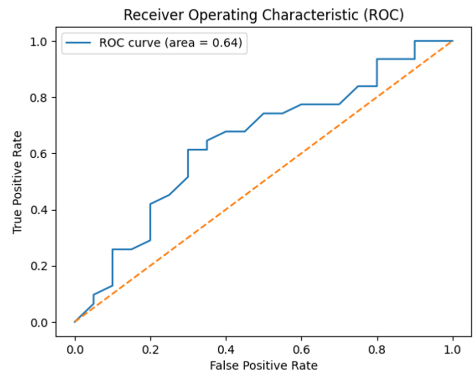

Figure 7: ROC Curve of Prediction Model

- Appendix.B

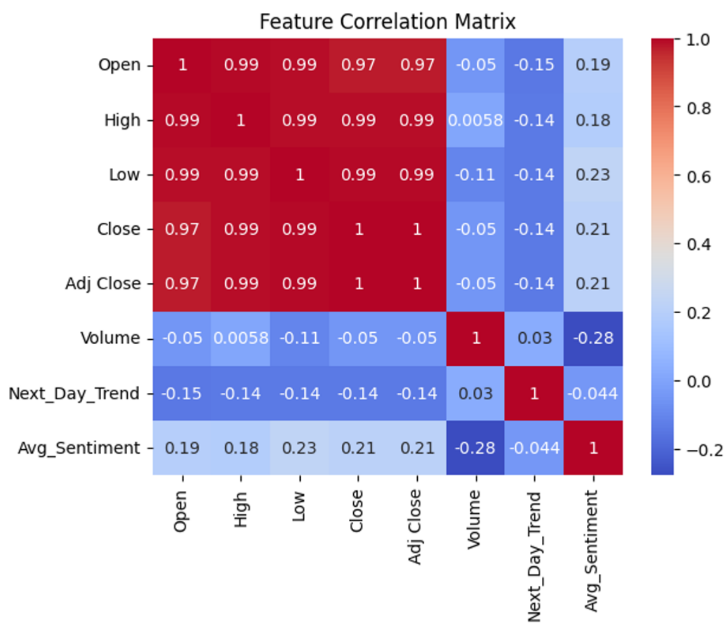

Figure 8: Feature Correlation Matrix of Prediction Model