DEEP LEARNING FOR ENHANCED TESLA STOCK PRICE PREDICTION: INTEGRATING TRADING DATA WITH TWEETS

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ABSTRACT

The project aims to predict Tesla's stock prices using tick data and Elon Musk's tweets. We segment the tick data into five time intervals and compare the performance of price prediction between different time intervals. Additionally, we incorporate features such as the number of likes and sentiment scores extracted from Elon Musk's tweets, given his influence on Tesla and the potential impact of his tweets on the company's stock price. We use Long Short-Term Memory Networks (LSTM) for their ability to work with time series data. Instead of predicting the price of a time point, we dynamically update the input of the testing set to let our model predict stock prices over a period of time. Furthermore, we compare it with the popular non-deep learning time series model, Prophet. The results show that the features extracted from the tweets is not sufficient to improve prediction, and the LSTM model demonstrates a markedly better prediction ability than Prophet.

1 INTRODUCTION

Social platforms have a significant impact on society, both reflecting and affecting public sentiment. According to a report published by The New York Times, Tesla's stock price is potentially affected by tweets from its CEO, Elon Musk (1). In light of this, our project aims to predict Tesla's stock prices by analyzing trading data and incorporating features derived from Elon Musk's tweets.

1.1 MOTIVATION AND APPROACH

Our motivation is driven by the interest in uncovering the factors that influence stock prices. To this end, we intend to employ deep learning techniques, specifically Long Short-Term Memory networks (LSTM) and Natural Language Processing (NLP), to analyze trading data and the impact of Elon Musk's tweets on stock price.

2 RELATED WORK

Elon Musk and Tesla's stock price have always been popular topics for in-depth analysis. Our research indicates that there is a substantial amount of work based on stock prices and Twitter data. For instance, the paper 'Predicting stock price using sentiment analysis through Twitter data,' authored by students at the Ramaiah Institute of Technology, employed the random forest machine learning model in their research. They found that using a random forest model is the most cost-effective approach (2). In another study, 'CEO's Tweets and Firm Stock Returns: A Case Study of Elon Musk and Tesla' by Jauron G. Dam, the focus was on Tesla's abnormal returns. This study found that a higher frequency of tweets correlates with periods of negative abnormal returns. It also noted that greater social media pessimism is linked to negative abnormal returns, fewer CEO tweets, and increased internet search interest in Musk-Tesla-Twitter terms (3). Furthermore, K.D. Knipmeijer's paper 'The Effect of CEO Tweets on the Stock Market Activity' employed statistical methods and proposed several hypotheses to test their predictions. This research concluded that there is no consistent evidence that Twitter use by CEOs increases the risk of stock volatility. In fact, it slightly suggests that it might reduce the risk (4).

However, the majority of existing research primarily utilizes machine learning methods or statistical approaches, training models to make predictions for specific points in time rather than over a period. In our research, we not only aim to improve the prediction by integrating tweet-related features but also shift the focus towards training deep learning models for predictions across time periods. We intend to evaluate the performance of deep learning models and compare results with a popular time series model, Prophet, that also predicts results for a period of time.

3 METHODS

3.1 LONG SHORT-TERM MEMORY NETWORKS (LSTM)

Long Short-Term Memory Networks (LSTM) are renowned for their ability to capture long-term dependencies and patterns in time-series data. This capability is crucial for accurate stock price prediction, particularly given the temporal nature of trading data.

3.2 NATURAL LANGUAGE PROCESSING (NLP)

Natural Language Processing (NLP) will play a pivotal role in processing and analyzing textual data, such as Elon Musk's tweets. It will convert this data into a format that can be seamlessly integrated with trading data. Leveraging NLP, our goal is to assess the influence of these tweets and evaluate their potential impact on Tesla's stock prices.

3.3 FACEBOOK PROPHET

We have adopted the open-source library Prophet, developed by Facebook, for our forecasting needs. Prophet excels in managing time series data, accommodating features such as seasonality and holidays effectively. This approach is applied to analyze stock price data, aiming to enhance the accuracy of our predictions.

4 EXPERIMENTS

4.1 DATA DESCRIPTION

- Tesla Stock Data:

  we have collected Tesla's 30-minute tick data, including timestamp, opening, high, low, closing prices, and volume, from Dec 1, 2011 to Auguest 27, 2021. Given the high noise inherent in high-frequency trading data, we applied a simple moving average (SMA) to smooth the stock data. We selected five SMA time intervals — 30 minuntes, hourly, daily, weekly, and monthly to discern trends across different timescales.

  Correlation matrices for each time interval were plotted(Figure 1). It reveal a perfect correlation (value of 1) among the price columns (open, high, low, close). However, there is a overoll low correlation between price varaibels and volume. We also plot a line chart of closing price which show that closing prices for each time interval highlighted Tesla's stock's general upward trajectory.(Figure 2)

  Observed from Figure 2 it is evident that the stock price underwent significant changes or improvements across all time intervals following the emergence of COVID-19 and its subsequent impact on people's lives. To exclude the impact of COVID-19, we decided to focus on the dataset ranging from December 1, 2011, to December 31, 2018, for our project.

- Twitter Dataset:

  We have collected Twitter data covering the period from 2010 to 2022. To synchronize it with our tick data, we decided to use the subset starting from December 1, 2011, to December 31, 2018.

  - **Tweets:** The actual text content of each tweet.
  - **Date and Time Created:** The timestamp indicating when each tweet was posted.
  - **Number of Likes:** The count of likes received by each tweet.

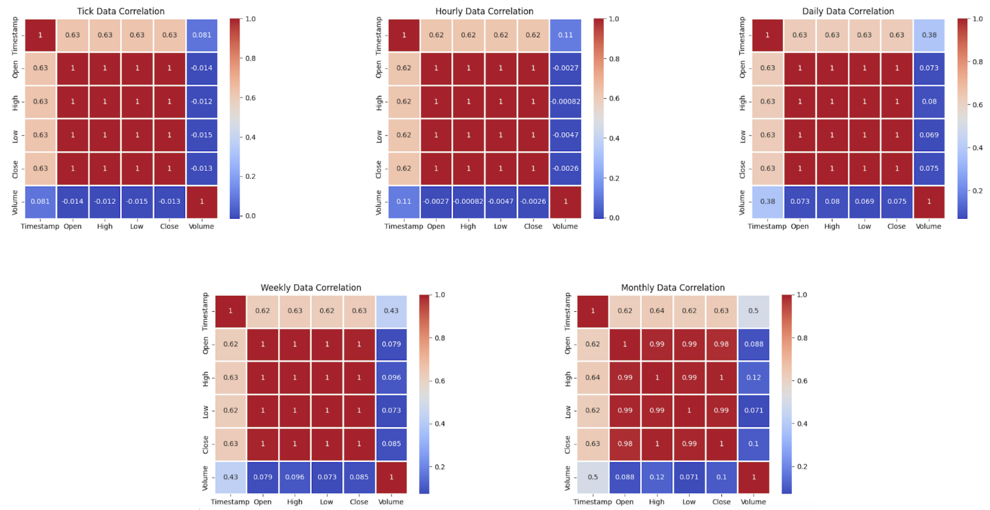

Figure 1: Correlation map of different time interval tick data

- **Source of Tweet:** The platform from which the tweet was posted, such as iPhone, web client, or other sources.

Considering the sentiment distribution in Elon Musk's tweets from 2011 to 2021, it is observed that 12.85% of the tweets exhibit negative sentiment, while there is an equitable distribution of positive and neutral sentiments, each approximately accounting for 44% (44.03% and 43.12%).

From the word cloud visualization of Elon Musk's tweets (Figure 3), words that appear more frequently are displayed in larger font sizes. Prominent words that frequently occur in his tweets include 'Tesla', 'amp', 'Yes', 'car', 'SpaceX', 'good', 'make', 'need', etc.

4.2 Preprocessing

4.2.1 Twitter Dataset

In order to enhance the clarity and utility of the Twitter dataset for model application, we undertook several preprocessing steps. These included renaming columns for improved readability, splitting the 'Timestamp' into separate 'Date' and 'Time' columns, and removing the 'Source of Tweet' column, which was deemed unnecessary for our analysis. We also added new columns such as 'text_char_count' and 'text_words_count' to provide additional insights into the tweet characteristics.

The preprocessing of the tweet text involved removing stopwords, links, emojis, punctuation, and other non-word characters to ensure a more focused analysis. Following this, we employed the BERT framework for sentiment analysis. The process involved tokenizing the text using the BERT tokenizer, predicting sentiment with the BERT model, and then converting the model outputs to probabilities using the softmax function. Additionally, we integrated emotion detection into our analysis. This involved loading a specific tokenizer and model designed for emotion detection (bert-base-uncased-emotion). The text was tokenized using this emotion detection tokenizer, followed by the prediction of emotions with the corresponding model. Similar to sentiment analysis, the outputs of the emotion detection model were also converted to probabilities using the softmax function.

After preprocessing, the dataset now comprises the following columns: 'num_of_likes', 'tweet_text', 'date', 'time', 'text_char_count', 'text_words_count', 'text_clean', 'sentiment_category', and 'polarity'.

4.3 Model training and Prediction

We divided the data into two sets: the training data spanning from December 1, 2011, to December 31, 2017, and the test data from January 1, 2018, to December 21, 2018.

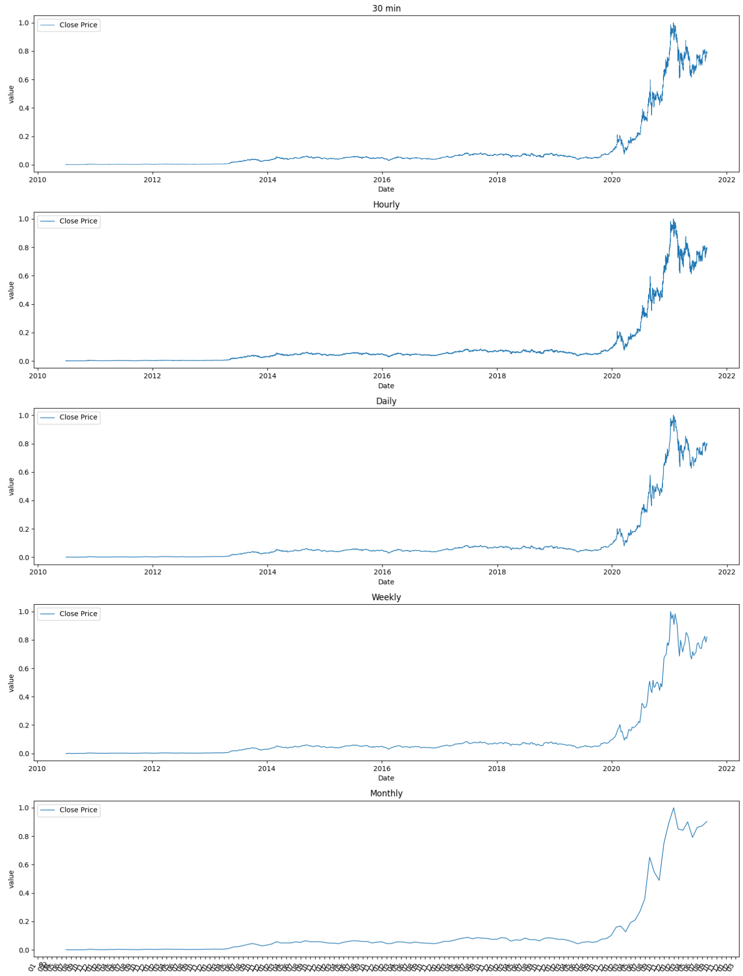

Figure 2: Close price line plot in different time interval

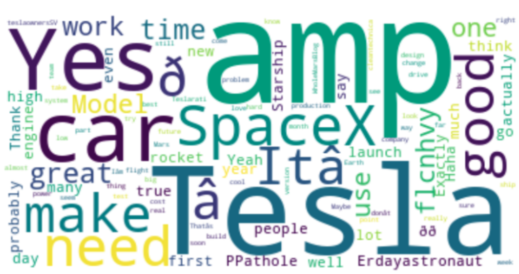

Figure 3: Word Cloud Highlighting the Most Frequent Terms in Elon Musk's Tweets.

- Stock Data:

  We use the 'Close' price of the stock to predict subsequent closing prices

- Stock data combine with tweet data:

  We use the 'datetime', 'num_of_likes', 'net_sentiment', and 'Close' to predict the closing price of the stock for subsequent periods.

4.3.1 LSTM

In this section, we fitted the LSTM model to five distinct time intervals and the combination of these different time intervals with tweet-related features separately. The architecture of the model is adapted from one employed in a similar forecasting project on Kaggle.(5) However, to facilitate a comparative analysis with the Prophet model, which is known for its ability to forecast over extended periods (e.g., 12 months), we revised the LSTM's prediction approach. Rather than predicting a single time point, our modified model is designed to forecasts over a specified period.

This approch was achieved by dynamically updating the test dataset after each prediction. For instance, if our test set encompasses 60 days for input, with each new price prediction, the oldest data point is removed, and the new prediction value is added to the test set. This method allows the LSTM model to continuously adapt and make predictions over a rolling period, similar to the functionality of the Prophet model.

4.3.2 Facebook Prophet

Upon training the LSTM model, we compared it with the another non-deep learning model, Prophet, also used for time series forecasting. Similar to our approach with LSTM, we evaluated two distinct datasets with the Prophet model: one consisting only of the monthly price data, and another that combined price data with tweet-related features.

4.4 Evaluation

For the evaluation phase, we set our model to forecast prices over a one-year interval following the end of the training dataset (testingg data). To evaluate the accuracy of our predictions, we employed the Mean Square Error (MSE) to quantify the difference between the actual and predicted stock prices. Furthermore, we plotted line plot of both the actual price and predicted price, allowing us to visually inspect the model's ability to track real-world price trends.The results of our analysis yield two key findings: firstly, only 30 minutes and monthly interval has a slightly improve after adding the tweet-related features. Secondly, for our specific task, the LSTM model markedly outperforms the Prophet model, demonstrating a superior ability in forecasting accuracy.(Shows in 4 to 15)

5 Conclusion

The project compares the impact of the tweet-related features on predictions across different time scales and the differences in predictive abilities between LSTM and Prophet models. Our result shows that the features we extracted from tweets and used in the models are not sufficient to improve the prediction of stock prices. More features from tweets or even other factors that may affect the stock price, such as political factors and the price of materials, should be considered. Moreover, our analysis revealed a notable difference in the Mean Square Error (MSE) between the LSTM and Prophet models. In the context of stock price prediction, the LSTM model demonstrated a better understanding of our dataset. This resulted in a markedly more robust predictive capability compared to the Prophet model, indicating a clear preference for LSTM in terms of accuracy and reliability in forecasting stock prices.

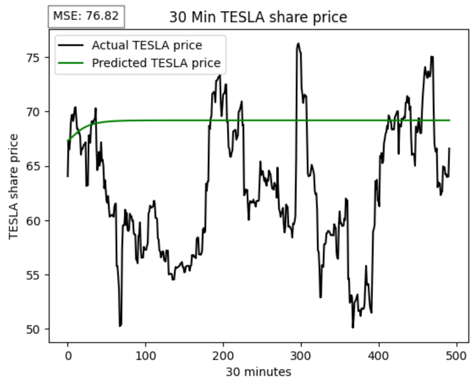

Figure 4: LSTM One year price prediction of 30 minutes time interval with tweet feature

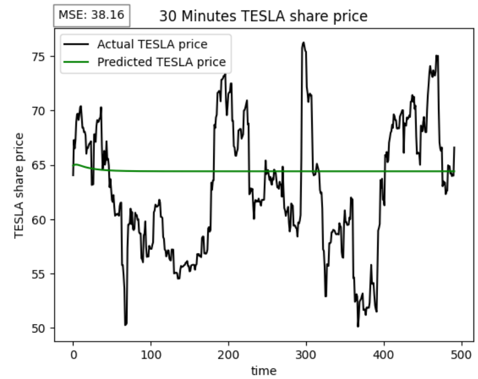

Figure 5: LSTM One year price prediction of 30 minutes time interval without tweet feature

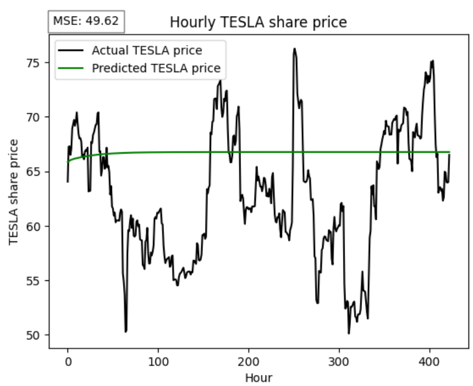

Figure 6: LSTM One year price prediction of hourly time interval with tweet feature

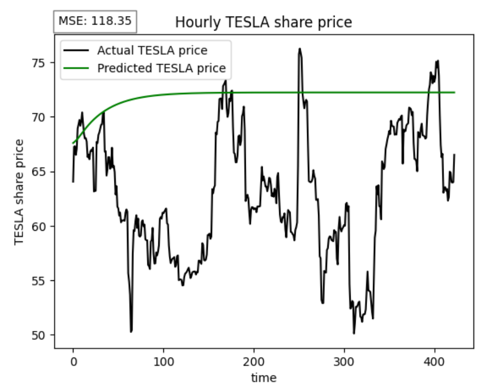

Figure 7: LSTM One year price prediction of hourly time interval without tweet feature

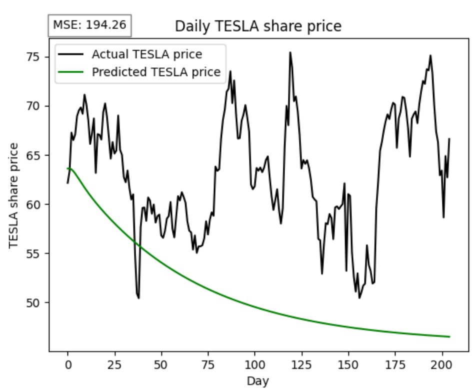

Figure 8: LSTM One year price prediction of daily time interval with tweet feature

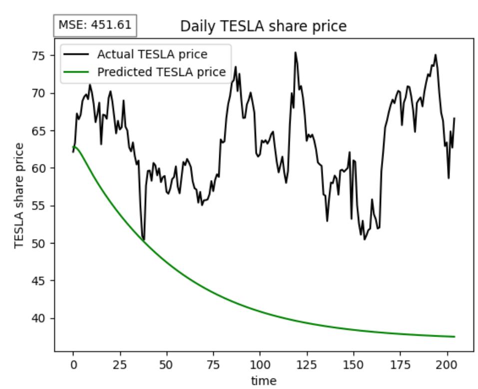

Figure 9: LSTM One year price prediction of daily time interval without tweet feature

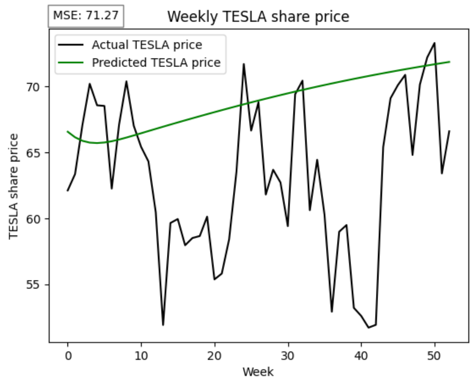

Figure 10: LSTM One year price prediction of weekly time interval with tweet feature

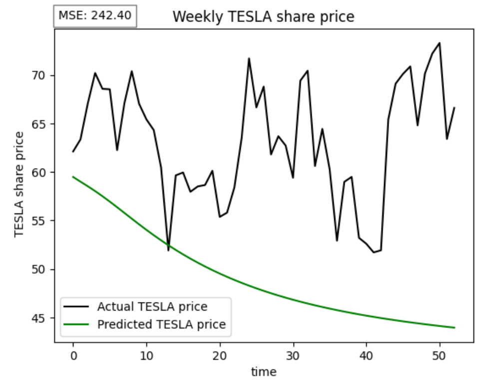

Figure 11: LSTM One year price prediction of weekly time interval without tweet feature

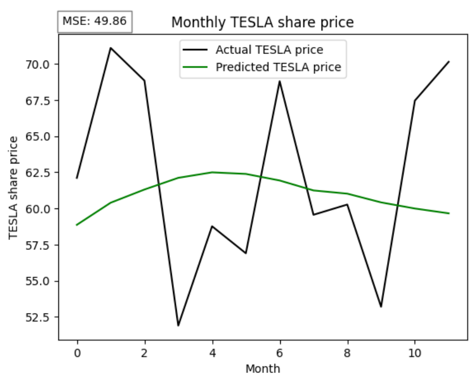

Figure 12: LSTM One year price prediction of Monthly time interval with tweet feature

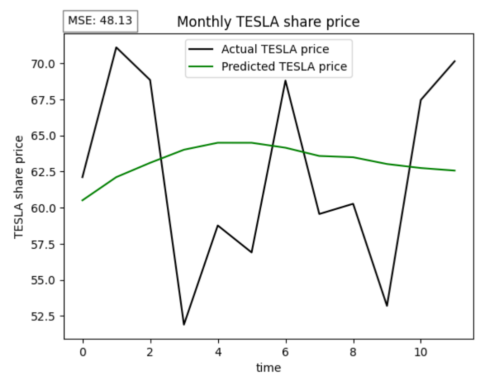

Figure 13: LSTM One year price prediction of Monthly time interval without tweet feature

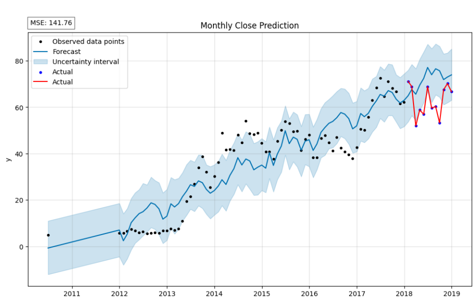

Figure 14: LSTM One year price prediction of Monthly time interval with tweet feature

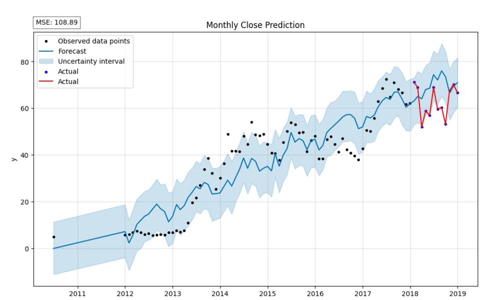

Figure 15: LSTM One year price prediction of Monthly time interval without tweet feature

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