ANALYSING THE REPUTATION OF TESLA USING SENTIMENT ANALYSIS

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Abstract

In today's competitive and data driven business environment, the reputation of corporations has evolved into a strategic concern for corporates. With the widespread access to information and the dominant role of social media in social exchanges in today's world, the task of upholding a business's reputation has transitioned into the digital space. This study aimed to understand the sentiments about the Tesla brand from tweets shared across the globe with the sole purpose of assessing what these sentiments are like in different countries, how they have evolved over time, and if they have any relationship with the price of Tesla stock. The VADER and Text Blob models were used to label the tweets. Also, VADER was used to compute sentiment compound scores of tweets which were then used to assess the evolution of sentiments and to calculate the correlation of sentiments with stock prices collected from Google Finance. The SVM, Bi-LSTM, and BERT models were also implemented to classify these sentiments and evaluate which of the models performs best. The results of the analysis showed that overall, there is a positive sentiment about the Tesla brand across the countries covered. Also, while the dominant sentiment is positive, when the Q4 2021 and Q4 2022 are compared, there was an increase in the number of negative sentiments about the company. The proportion of negative reviews among the total reviews was 11.9% in Q4 2021 vs 16.8% in Q4 2022. The findings also show that there is a moderate statistically significant correlation of 43% between Tesla stock prices and compound scores generated from sentiments. Finally, the BERT model performed the best in predicting the sentiments about the company with an accuracy of 96%, outperforming the SVM and Bi-LSTM models which had accuracy scores of 93% and 89% respectively.

Keywords: Tesla, Stock, Correlation, Musk, BERT, SVM, Bi-LSTM, Accuracy, ML, DL

Introduction

In today's competitive and data driven business environment, the reputation of corporations has evolved into a strategic concern for corporates. With the widespread access to information and the dominant role of social media in social exchanges in today's world, the task of upholding a business's reputation has transitioned into the digital space (Walker, 2010). The use of social media across most areas of human lives today has elevated the significance of handling corporate reputation while making it more challenging. This is because, real-time views from employees, clients, suppliers, and users can shape a company's image (Al-Yazidi et al., 2022), and corporates are increasingly concerned about uncontrolled information dissemination and opinions within online communities. Moreover, companies now recognize the importance of leveraging their reputation for valuing intangible assets and drawing financial support (Colleoni et al., 2013), and actively look to understand and assess their reputations. Given that the reputation of an organization has transformed into a precious resource, this is prompting companies to dedicate significant financial and human resources towards its cultivation and ongoing preservation (Fombrun, 2005; Colleoni et al., 2013; Al-Yazidi et al., 2022).

Online reviews shared by various stakeholders about a product or organization play a vital role as electronic word-of-mouth, with negative or positive statements made by new leads or current and past clients, or employees about products and companies (Hennig-Thurau et al., 2004). For modern day consumers, these reviews are key to the decision-making process when any type of purchase decisions are being made. Therefore, positive news and reviews about a company can boost brand value, leading to increased sales. Also, the reputations of companies can typically receive a boost due to these positive reviews whereas negative reviews have the opposite effect of reducing sales and diminishing brand value (Litvin & Hoffman, 2012; Bhandari & Rodgers, 2017). Therefore, addressing negative comments in a timely manner is important for corporates (Wu & Yang, 2010; Bhandari & Rodgers, 2017; Crijns et al., 2017; Roy et al., 2017; Sijoria et al., 2018; Lee et al., 2019).

Detecting and promptly addressing comments which can negatively affect a brand's reputation is a significant challenge. Due to progress in Deep Learning (DL) and Natural Language Processing (NLP) technologies, several researchers have developed models which aim to extract polarity from opinions shared on platforms such as Twitter allowing for a situational and time bound reputational assessment of a brand.

Research objectives

The proposed study will aim to use sentiment analysis techniques to gauge public opinion about Tesla. Accordingly, the research questions to be investigated include:

i. What is the prevailing sentiment on Twitter across different geographical regions?
ii. How have sentiments towards Tesla evolved over specific time periods?
iii. Is there a correlation between sentiment towards Tesla and its stock market performance?
iv. Is the performance of traditional Machine Learning (ML) models generally better than DL and Transformer models when classifying sentiment from tweets?

Background

The evolving nature of the internet and its role in disseminating information about brands underscore its increasing importance in the broader landscape of financial analysis and decision-making. Yet, efficiently determining the relationship between sentiments from clients and customers is a topic researchers continue to explore, with some evidence that public opinion have an impact on the financial performance in public financial markets (Az-Zahra et al., 2021). In their study, Az-Zahra et al. (2021) explored the possibility of using news headlines and data from social media platforms to support investment thesis on Chrysler, Volkswagen, and General Motors. The researchers obtained stock price data from the World Stock Price Index and used the VADER lexicon model to compute daily compound scores for the collected social media data. To investigate the relationship between sentiment and stock performance, the researchers used the Pearson correlation. The findings indicated statistical significance in sentiment-stock performance correlations, with p-values of 0.016 for Volkswagen, 0.002 for Chrysler, and 0.038 for General Motors based on the data gathered from Twitter. Similarly, Maqbool et al. (2023) used VADER, Text Blob, and Flair models to generate sentiment scores, which was then summed up as a feature score to assess the impact of financial news on stock prices. The MLP regressor was used for predictions and it incorporated input combinations, including sentiment scores, closing prices, normalized historical data, and two additional features - Trend and Future Trend. The combination of financial news sentiments and MLP-Regressor demonstrated a 90% accuracy in predicting stock prices, revealing a significant correlation between stock prices and financial news.

Several researchers have conducted studies to classify tweets and customer reviews based on the polarity in the texts in addition to comparing the performance of the BERT transformer models versus other DL and ML models. González-Carvajal and Garrido-Merchán (2020) compared seven models which were trained and tested using 50,000 IMDB movie reviews. The authors aimed to see if the Voting Classifier, Logistic Regression, Support Vector Machine (SVM), Multinomial Naïve Bayes, Ridge Classifier and Passive Aggressive Classifier would perform better than the BERT model. The hypothesis that the BERT model would perform better was validated as it returned the best accuracy of 93.9%. Nugroho et al. (2021) also compared the performance of ML models and BERT models using a dataset of user reviews collected from Google Play store. The researchers compared the results of labels from the ratings shared by the users and labels assigned from the InSet lexicon model. Their results showed that the IndoBERT variation of the BERT model outperformed the ML models and had an average accuracy score of 82.5%. The Lexicon based labelling also had much better accuracy compared to labels derived from the ratings. Similarly, Patel et al. (2023) compared the performance of K-Nearest Neighbour (KNN), SVM, Decision Tree, Logistic Regression, Random Forest, Adaboost and BERT models used to classify sentiment from a dataset of reviews shared by airline passengers. The BERT model recorded the highest accuracy score of 83% outperforming all other models.

This study addresses a gap in existing research by focusing on sentiment analysis related to Tesla, the Electric Vehicle (EV) company. While prior studies have explored sentiments' impact on financial performance and compared ML and DL models for sentiment classification on corporate reviews, none have specifically covered Tesla. The company has faced negative media attention due to its CEO Elon Musk's actions prompting customer dissatisfaction and concerns about shareholder impact, with some customers declaring that they were ashamed of the brand and driving the Tesla vehicle (Shaban, 2023; Sherman & Hussain, 2023). Given that most countries across the world are beginning to set policies which would phase out the use of automobiles powered by fossil fuel, this should be a significant opportunity for the company. Therefore, it is imperative to assess public opinion about the company as it currently holds a 13% market share of global EV market (Statista, 2023). This would help gauge the future outlook for the company.

Methodology

Tesla Data Acquisition

The data used for this study was collected Twitter. A total of 56,591 tweets were collected for the periods between September 30, 2021, and December 31, 2022. The keywords used when extracting the data included #Tesla, #Teslamotors, #Teslamodels, #Teslastock, #Tsla and the focus was on collecting tweets in English Language. In addition to the tweets collected, Tesla closing stock price data was collected for the period between October 1, 2021, and December 31, 2022, from Google Finance.

Text cleaning

The data cleaning and text processing stage involved cleaning and preparing the data to be used in Sentiment Analysis models. For high quality results, it is important to consider the steps taken to preprocess a dataset as the order and selection of preprocessing steps greatly determine the final results (Verma et al., 2011; Havas & Resch, 2021). For the lexicon models, data cleaning was carried out using the approach suggested by Waterman (2022) and Hutto and Gilbert (2015) which included keeping uppercase characters in the tweets as this signifies text intensity when sentiments are assigned. Furthermore, all punctuations were removed except question and exclamation marks. Emojis were also not removed. The remaining text preprocessing actions that were implemented include:

- Removing hashtags, usernames, URLs, and HTML links from tweets
- Removing special characters
- Removing stopwords in tweets except the word "but" as suggested by (Hutto & Gilbert, 2015)
- Expanding English language contractions
- Lemmatizing of words in the tweets

For the ML and DL models the actions listed above were carried out in addition to lowercasing all texts, removing emojis, and all punctuations and stopwords without exception this time. For the BERT model, the actions were limited to removing hashtags, usernames, URLs, and HTML links from tweets.

Data Labelling

The data collected from Twitter did not contain labels, however supervised learning requires the availability of labels which are then used to train models. For this study, 3 different approaches were considered and used to label the tweets. This include manually labelling a subset of the dataset – in this case a total of 1,506 tweets were manually annotated with labels including positive, negative, and neutral. In addition to this, Lexicon unsupervised ML models, VADER and TextBlob were used to label the data. The manually labelled data was taken as the ground truth and the results of the Lexicon models were compared to these labels. The approach of labelling tweets with lexicon models is consistent with techniques used by Sitorus et al. (2023), Alenzi et al. (2022) and Nurcahyawati and Mustaffa (2023).

Lexicon Models

Valence Aware Dictionary and Sentiment Reasoner (VADER) (Hutto & Gilbert, 2015) is a lexicon and rule-based approach that employs a well-established sentiment lexicon of around 7,500 features, graded from −4 to +4, spanning extremely negative to extremely positive. Computationally, VADER determines sentence polarity by summing sentiment scores of all words, followed by normalizing the polarity score to the range of −1 to +1 (Pano & Kashef, 2020; Chiny et al., 2021; Pam et al., 2022; Isnan et al., 2023). Equation 1 presents the formula for VADER.

$$\boldsymbol{x = \frac{x}{\sqrt{x^2+\alpha}}}$$ **Equation 1**

x is the score assigned to words and α is the normalizing constant.

The Text Blob model determines the polarity value of sentences, where this value can be between −1 and 1. Then it can be used to label the data with the right sentiment value (positive, negative, or neutral) (Nemes & Kiss, 2021).

Sentiment Classification Using ML and DL Models

SVM, Bidirectional Long Short-Term Memory Network (Bi-LSTM), and Bi-directional Encoding Representation for a Transformer (BERT) (Devlin et al., 2019) were trained to predict the sentiment in the tweets. The Term Frequency – Inverse Document Frequency (TF-IDF) technique was used to extract features and used in the SVM model. In addition, Random Search hyperparameter optimization was used to find the best parameters for the model. For the Bi-LSTM model, word embedding techniques such as Word2Vec, Glove and Fasttext were used to extract features.

Experiments

All experiments were done using Python and with Jupyter notebook. The first set of experiments focused on the correlation between stock price movements and sentiment from tweets, while the second group involved training supervised learning models to classify tweets by sentiment. The collected Twitter dataset did not contain sentiment labels, prompting a two-step approach to address this including generating labels using VADER and Text Blob lexicon models, and retaining rows where both models agreed on the sentiment. This resulted in 24,604 tweets for the final analysis (down from 56,951). Also, manual labels were assigned to 1,506 tweets and used to validate the labels returned by the lexicon models. Figure 1 shows the count of labels from VADER and Text Blob.

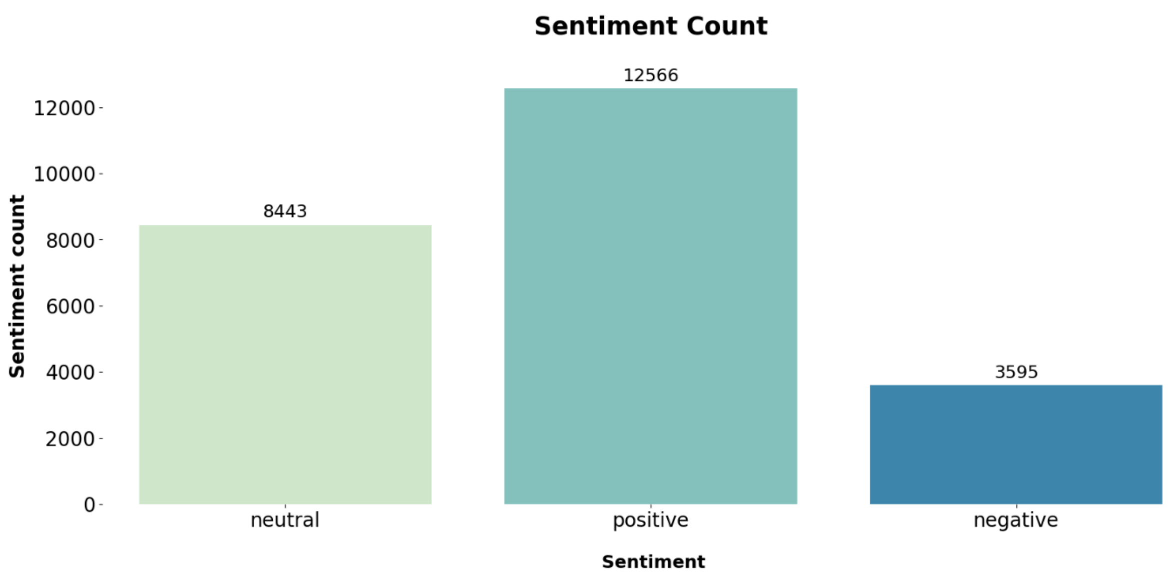

Figure 1: Count of labels from VADER and Text Blob

VADER was also used to generate the compound score for each tweet and thereafter daily average compound scores were computed. Pearson correlation coefficient analysis was performed using this daily average compound score in conjunction with Tesla daily closing stock prices, with the p-value measure of statistical significance used to assess the correlation coefficients. For the second group of experiments, SVM, Bi-LSTM, and BERT models were used to classify tweets. For the SVM and Bi-LSTM models, training was done using 70% of the data and 30% for testing, while it was 80% vs 20% for the BERT model.

The SVM model used TF-IDF for feature extraction and the parameters after optimization were linear kernel, gamma of auto and C of 10,000. Four experiments were conducted using the Bi-LSTM models including using the Keras embedding layer, Word2Vec, Glove and Fasttext. The models contained an embedding layer with output dimension of 100, two Bi-LSTM layers of 128 and 64 units, this is followed by a dropout layer of 0.2, and a dense layer of 256 units with ReLu activation. The final output layers contain 3 classes and the SoftMax activation function. The model, compiled with Adam optimizer with a learning rate of 0.0001, was trained for 30 epochs with a batch size of 128. For the word embeddings, in the case of Glove, 100 dimensional Glove embedding was used and this was collected from the Pennington et al. (2014) website. The Python Genism library was used to initialize the Word2Vec embeddings, and this was also set to 100 dimensions. In the case of Fasttext, the Skip-gram model was trained using 100 dimensions as well. The BERT model was initialized using Hugging Face Transformers in TensorFlow. The pooled output of the BERT model had a dropout layer of 0.5, followed by a fully connected dense layer of 128 neurons with tanh activation function. This is followed by another dropout layer of 0.2, the final dense layer which contains 3 neurons, and which used the SoftMax activation function. The Adam optimizer was used, with training done over 5 epochs, a batch size of 32 and a learning rate of 0.0001.

Evaluation Metrics

Accuracy, precision, and recall were all used to evaluate the performance of the models. Accuracy measures the correct classification proportion across all classes, reflecting the overall classifier performance. Recall assesses the ratio of correctly predicted positive tweets to all actual positives. Precision on the other hand represents the accuracy of the positive predictions made by the model, indicating the proportion of true positive predictions among all instances predicted as positive. (Cai et al., 2020; Xie et al., 2020; Li et al., 2021). Equation 2 to Equation 4 presents the formula for accuracy, precision recall and F1-score respectively.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TN+TP}}{\boldsymbol{TN+TP+FP+FN}}$$ **Equation 2**

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{FP+TP}}$$ **Equation 3**

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{FN+TP}}$$ **Equation 4**

Results

What is the prevailing sentiment on Twitter across different geographical regions?

The United States of America (USA) had the highest number of tweets with 5,293, followed by India (1,501), the United Kingdom (UK) with 1,446 tweets, Canada with 768 and France with 320. Figure 2 presents the count of tweets by country.

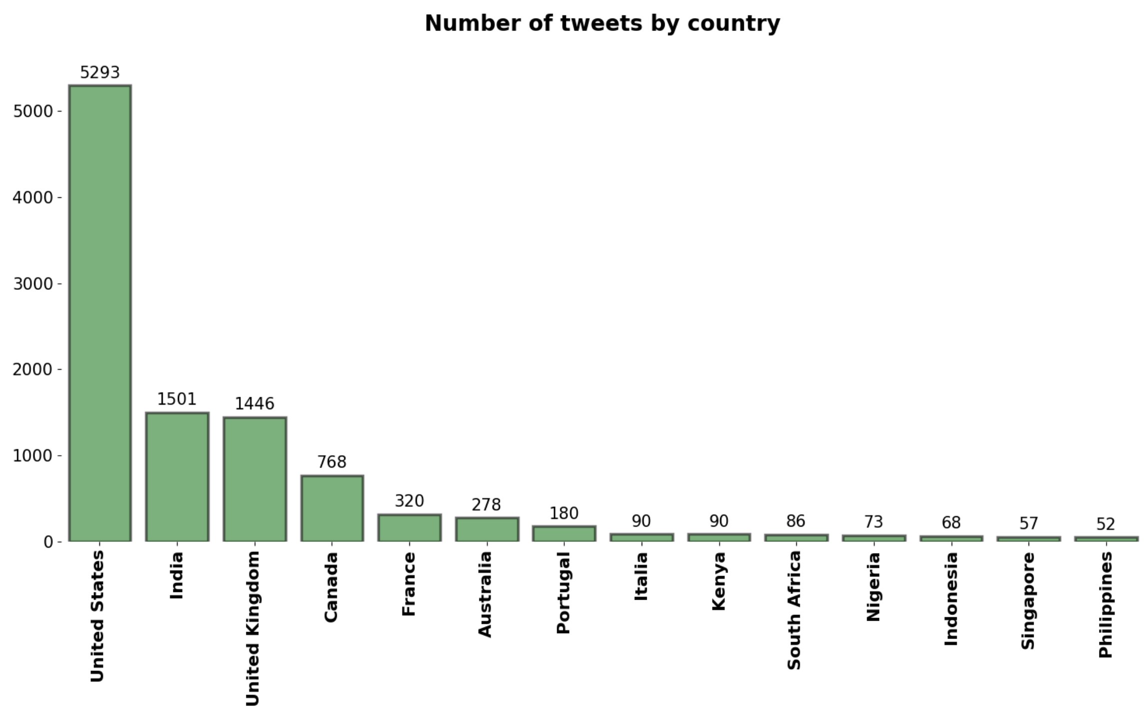

Figure 2: Counts of Tweets by Country

Figure 3 presents the overall compound score by country and indicates the intensity of sentiments coming from each country based on the tweets. Kenya which had just 90 tweets had the highest overall compound score of 0.47 and this is followed by Nigeria with a compound score of 0.39 (73 tweets). While there was a small size of data coming from African countries (Nigeria, Kenya, and South Africa), these countries had the highest average compound scores when compared to other continents. The USA with the most tweets had a compound score of 0.24.

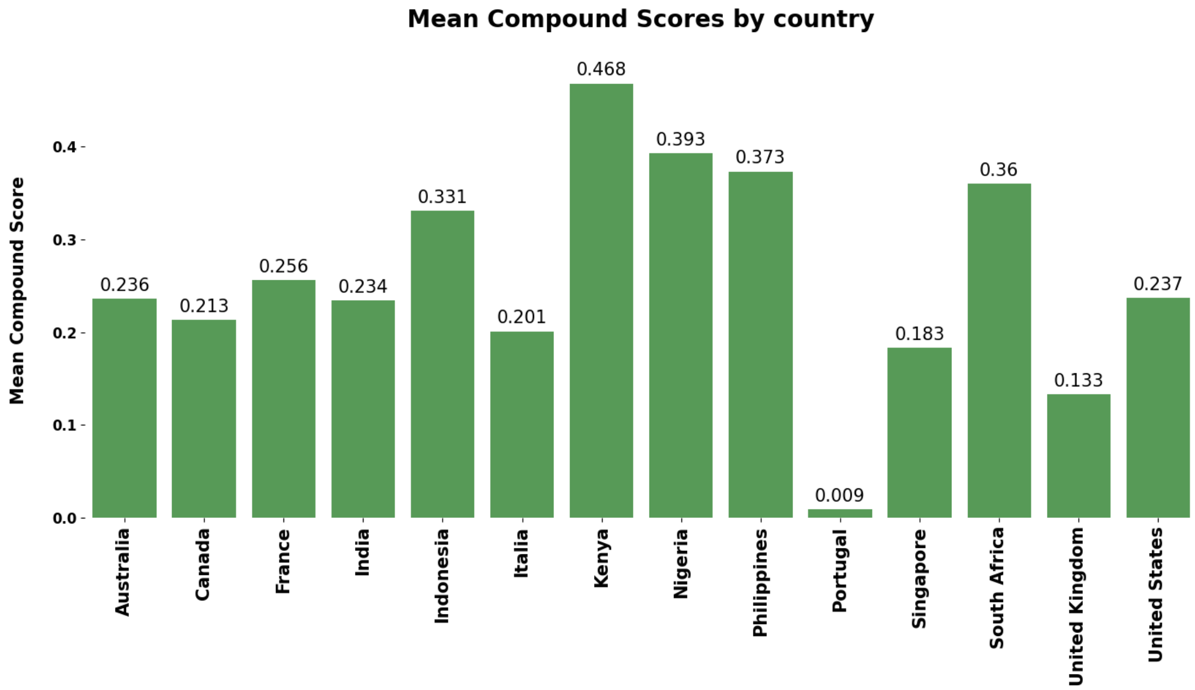

Figure 3: Mean Compound Scores by Country

Figure 4 presents the average compound score by country between October 2021 and December 2022. Portugal, France, and the USA notably had a recurring pattern of sentiment fluctuations over the period analysed. For example, in the case of the USA, in October 2021, the compound score was 0.37, this dropped to 0.13 in February 2022, increasing again in April 2022 before dropping down to 0.18 in June 2022.

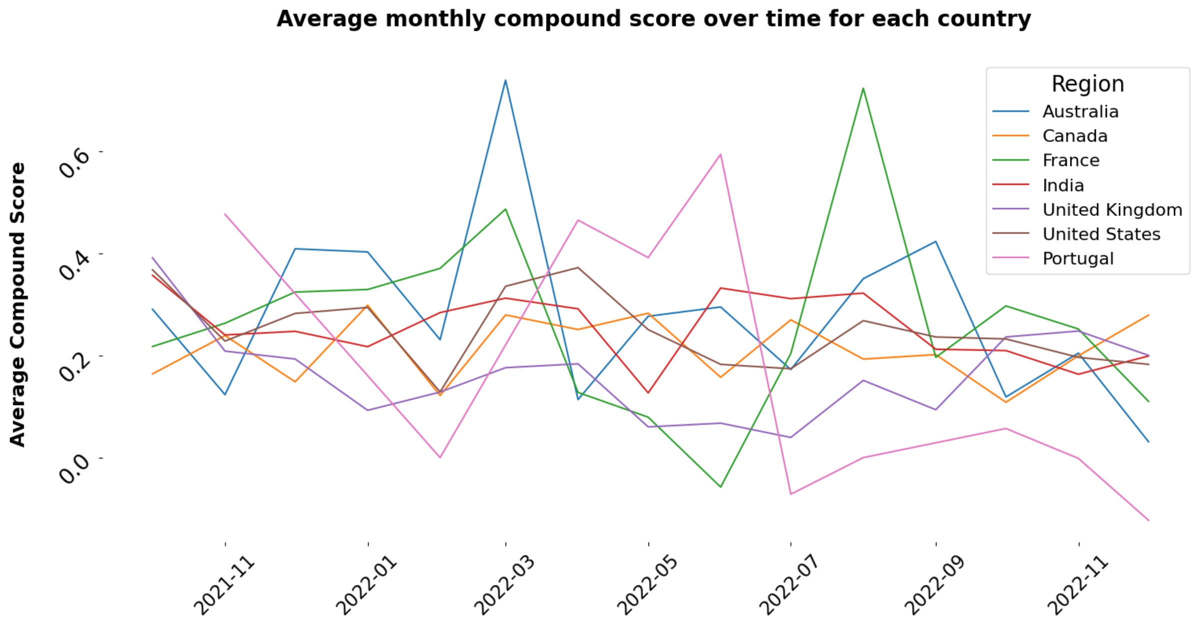

Figure 4: Average monthly compound score for each country

How have sentiments towards Tesla evolved between October 2021 and December 2022?

Put side by side, October to December 2021 had few negative sentiments compared to the same period in 2022, with 6.3% of tweets being negative in October 2021 vs 13.4% in October 2022. This can be seen in the split of sentiments in Figure 5.

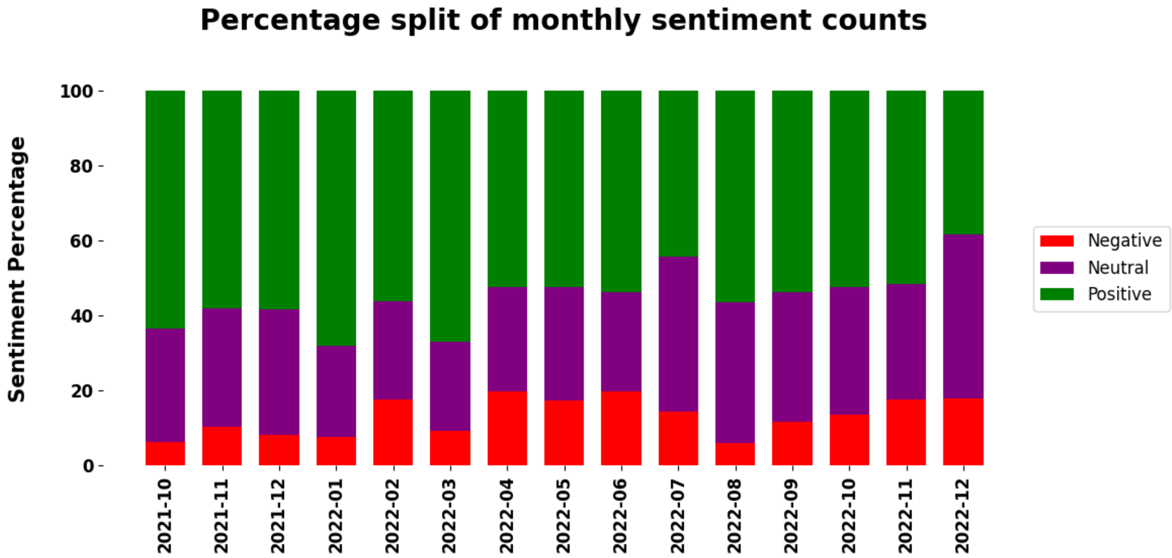

Figure 5: Monthly split of sentiments

This was the same for November 2021 vs 2022 with 10.3% and 17.5% respectively, and 8.0% vs 17.8% in December 2021 and 2022 respectively. The same could be observed in the number of positive tweets with the last quarter of 2021 containing more proportion of positive tweets vs the same period in 2022. This trend is also apparent in the average monthly score presented in Figure 6, showing a decline in scores between the periods in 2021 and 2022.

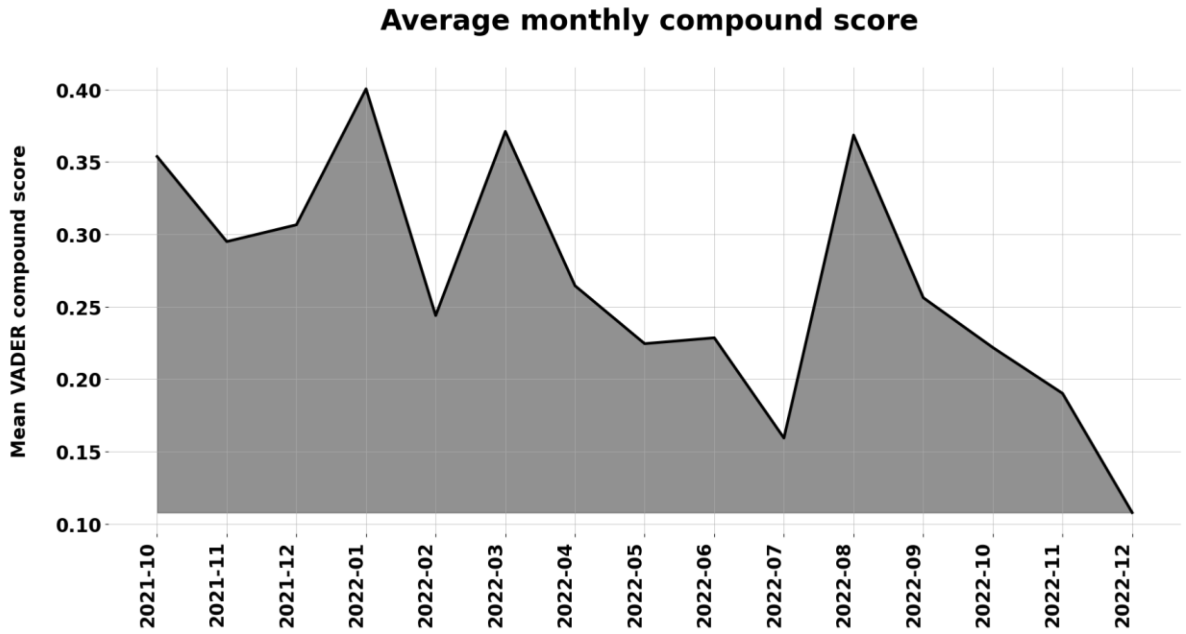

Figure 6: Average monthly compound score

Is there a correlation between Tesla stock prices and the sentiment extracted from tweets about Tesla between October 2021 and December 2022?

The observed correlation between Tesla stock prices and overall compound score was 43% with a p-value of 0.000000000000003. This affirms that there is statistically significant correlation between closing stock prices of Tesla and the sentiments observed through the compound score. Figure 7 shows the movement in Tesla closing stock prices and the average daily compound score over the course of October 2021 and December 2022.

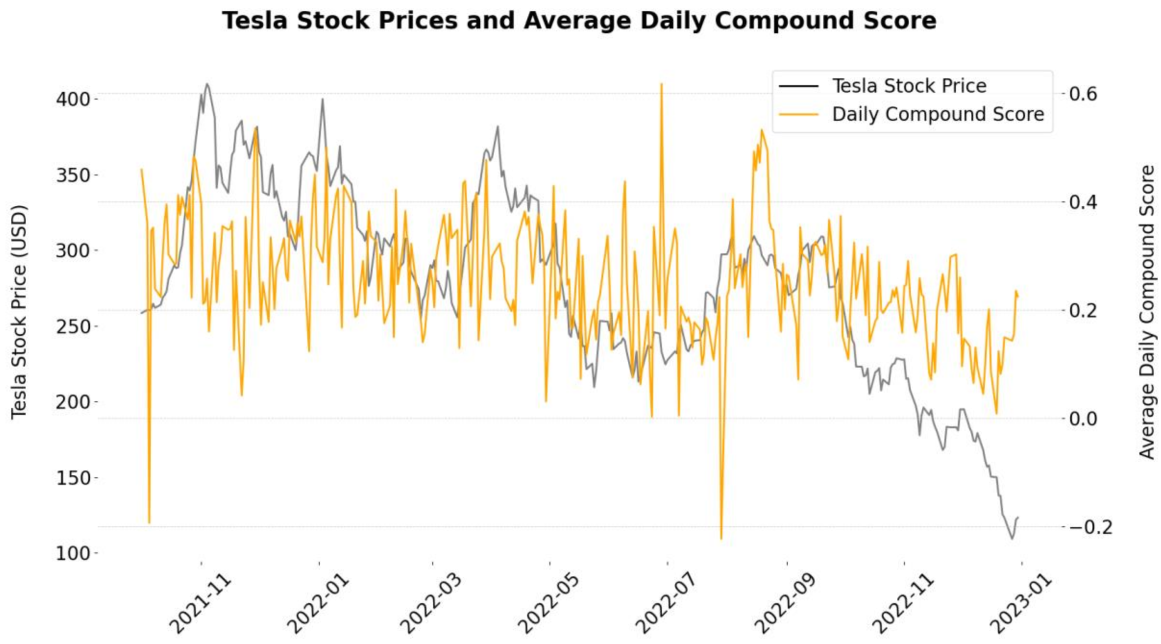

Figure 7: Tesla closing stock price movement and average daily compound score

Results of the ML models for classifying tweets

The SVM recorded an impressive overall performance with 93% accuracy, outperforming all the Bi-LSTM models. However, BERT model had the best accuracy score of 96% with precision and recall of 95% and 94% respectively, both of which were better than results of the other models.

Table 1: Sentiment classification results

Models	Accuracy	Precision	Recall
SVM	93%	91%	92%
Bi-LSTM	81%	73%	71%
Bi-LSTM with Glove	89%	87%	85%
Bi-LSTM with Word2Vec	84%	78%	80%
Bi-LSTM with Fasttext	81%	73%	72%
BERT	96%	95%	94%

Discussion

This study aimed to investigate the sentiment on Twitter across geographies, how these sentiments towards Tesla varied over time and determine whether the sentiment towards Tesla correlates with stock price movements. It also explores whether transformer models are better than traditional ML and DL models in classifying sentiments derived from tweets. The results showed that across the board all the countries had positive compound scores, depicting positive sentiments about Tesla. Periods of downward or upward trends in sentiment (as presented in Figure 6) appeared to be linked to either the actions of Elon Musk in other business ventures or the decisions made by the board of directors of Tesla. For example, in January 2022, following news that Elon Musk was showing interest in investing in Twitter (Zahn, 2022), the compound score for Tesla plunged from 0.40 to 0.25. Similarly, the downward trend in compound score seen in April 2022 could be attributed to news that Elon Musk had finally agreed to invest in Twitter (Bursztynsky & Kolodny, 2022). These events were also followed by a fall in stock price and in particularly, the announcement in April 2022 was followed by a 12% fall in the price of Tesla stock. Conversely, sentiments about the company improved in August 2022, following the announcement of a stock split (Kolodny, 2022), which saw compound score increase sharply from around 0.15 to 037.

A moderate correlation of 43% was observed between compound score and stock prices, supporting the existence of a relationship between stock price movements and sentiments in social media data. The correlation between sentiments and stock price movement is consistent with the results of Az-Zahra et al. (2021) whose study showed a statistical significance in sentiment-stock performance correlations, with p-values of 0.016 for Volkswagen, 0.002 for Chrysler, and 0.038 for General Motors based on the data gathered from Twitter. Also, when periods are isolated the announcement in August 2022 of a stock split saw a 52% correlation between compound score and stock prices with a p-value of 0.02.

The results of the VADER and Text Blob models were compared to the manually labelled data and this was done to assess the quality of the results from the lexicon models and also to validate the results of the analysis conducted using the VADER compound score. The VADER labels had a 93% accuracy vs the manual labels, with precision and recall scores also 93%. Figure 8 presents the confusion matrix of the VADER model validated against the manual labels. The high accuracy score can be construed to give credence to the analysis conducted using the compound score.

BERT-based models have gained substantial recognition for their superior performance in various classification tasks, and this was validated by the results of the experiments conducted in this study. The model achieved an accuracy score of 96% outperforming the results of the SVM and Bi-LSTM models. The results of the models are consistent with the findings of González-Carvajal and Garrido-Merchán (2020) whose BERT model achieved an accuracy of 94% outperforming ML models used in their study. Yet, the performance of their BERT model was slightly lower than the 96% achieved in this study. This is similar for the results obtained by the BERT model used by Nugroho et al. (2021) which achieved an accuracy score of 83%.

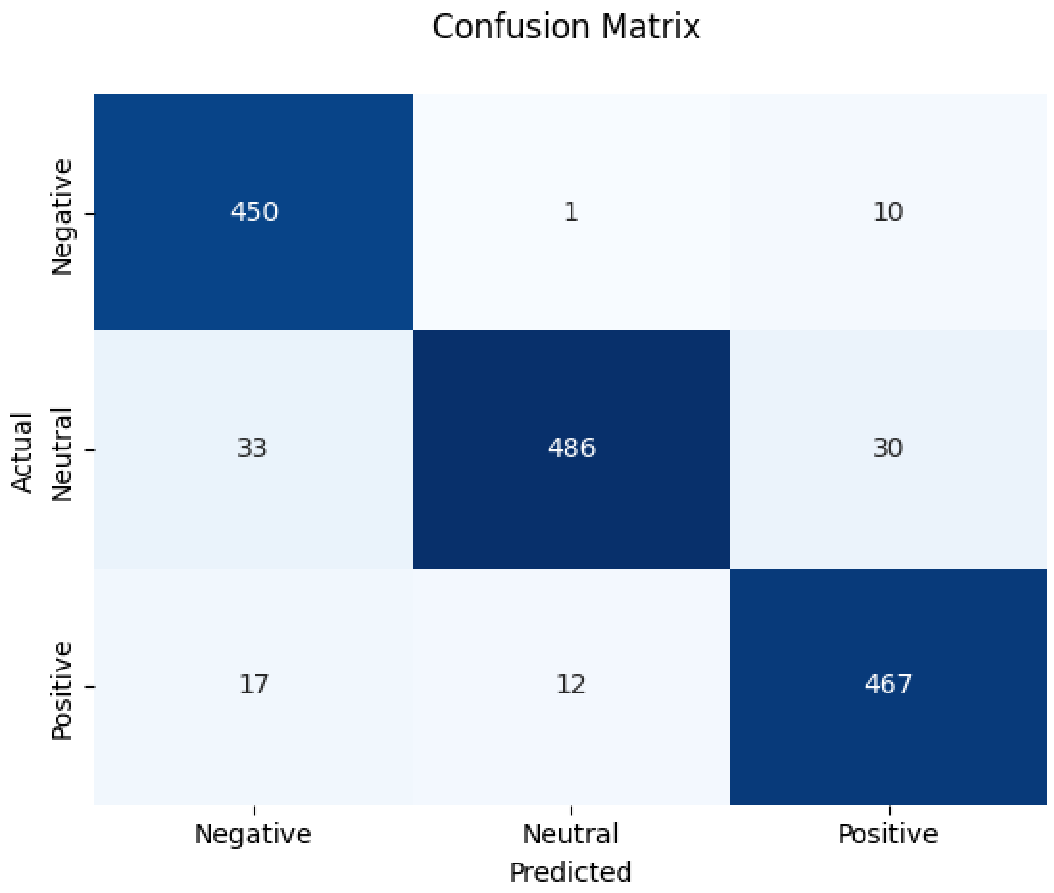

Figure 8: Confusion matrix of VADER labels compared to manual labels

The findings in this study underscores the growing influence of social media sentiments, particularly on Twitter, on companies' financial performance. It emphasizes the impact of the actions of key executives, even if unrelated to the company at hand, as seen with Elon Musk's influence on Tesla and Twitter. This implies potential financial implications for shareholders when the actions of key figures affect brand perception and investment returns. For Tesla, the study suggests that the founder's actions could play a pivotal role in shaping the company's long-term outlook.

Conclusion and Future Work

This study aimed to explore the sentiments about the Tesla brand across different geographies. Also, it assesses how these sentiments evolved over time in addition to evaluating if there is a correlation between sentiments about Tesla and its financial market performance. Furthermore, it looked into which models would perform best in predicting sentiments based on polarity. The results showed that overall, there is a positive sentiment about the Tesla brand across the countries covered. Also, while the dominant sentiment is positive, when Q4 2021 and Q4 2022 are compared, there was an increase in the proportion of negative sentiments vs all the sentiments about the company (11.9% vs 16.8%). The findings also show that there is a moderate statistically significant correlation of 43% between Tesla stock prices compound scores. Finally, the BERT model performed the best in predicting the sentiments about the company with an accuracy of 96%, outperforming the SVM and Bi-LSTM models which had accuracy scores of 93% and 89% respectively. The main limitation of this study was the lack of availability of a larger amount of labelled data which could have been used to fine-tune the BERT model and also train the ML and DL classifiers. For future work, the research about relationship between compound score and the daily, weekly, or monthly stock price volatility could be explored. Also, employing upsampling or down sampling techniques could help improve the performance of the Bi-LSTM models.

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