Available online at https://ejournal.corespub.com/index.php/ijmsc/index

International Journal of Mathematics, Statistics, and Computing

e-ISSN 3025-0803

Vol. 3, No. 3, pp. 81-87, 2025

Sentiment Analysis of Public Comments on the YouTube Video "Trump Unveils Sweeping Global Tariffs in Watershed Moment for World Trade" by BBC News Using the Long Short-Term Memory Method

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Abstract

This study aims to analyze public sentiment towards the announcement of global tariffs by the President of the United States, Donald Trump, using the Long Short-Term Memory (LSTM) method. The analysis focused on user comments from one video uploaded by BBC News on its official YouTube channel, titled "Trump Unveils Sweeping Global Tariffs in Watershed Moment for World Trade.". Sentiment analysis is performed by classifying public comments into positive or negative sentiment categories, through preprocessing stages such as case folding, cleansing, normalization, stop words, stemming and tokenization. The processed data is then used to train and evaluate the LSTM model, which is known to capture temporal relationships and contextual meaning in text data. The results showed that the sentiment was negative, with 64.6% of the comments showing negative sentiment and only 34.4% showing positive sentiment. The performance of this LSTM method gives a performance of 76% Accuracy with 77% precision, 84% recall, and 81% f1-score on negative sentiment and 74% precision, 64% recall, and 69% f1-score on positive sentiment. These findings demonstrate the public's critical view of Donald Trump's global tariff policy and confirm the effectiveness of the LSTM method in extracting sentiment trends from online discussions. This research contributes to the analysis of public opinion in the context of international economic policy.

Keywords: Long Short-Term Memory, Public Opinion, Sentiment Analysis, YouTube Comment

1. Introduction

The global tariff policy implemented in the Donald Trump administration created a public conversation that occurred in layers of society around the world (Boucher & Thies, 2019). This policy has created a lot of public opinion that President Donald Trump will start a trade war conflict with various countries, but there are also various public reactions that think it is a natural thing to happen. Therefore, analysing this public sentiment is important to understand the public's perception of the economic policy.

Along with the advancement of social media usage across all walks of life, sentiment analysis has become quite an important tool to understand public opinion. YouTube as one of the platforms with the largest video sharing service in the world not only provides information content, but also a space for discussion through the comment feature in each video, where these comments represent users' perceptions and emotions on an issue (Rotman & Preece, 2010; Madden et al., 2013)

In this context, the video entitled "Trump Unveils Sweeping Global Tariffs in Watershed Moment for World Trade" uploaded by the BBC News YouTube channel is the source of data in this study to assess the response to the global tariff policy. The analysis method used in this research is Long Short-Term Memory (LSTM). LSTM is a development of Recurrent Neural Network (RNN) that is effective in natural language processing and sentiment analysis because LSTM could overcome the vanishing gradient problem in sequential data processing (Hochreiter & Schmidhuber, 1997).

This study examines public sentiment toward President Donald Trump's global tariff policy by classifying YouTube comments into negative and positive categories and evaluating the performance of the LSTM model. By analysing sentiment distribution and model accuracy on large-scale text data, this research provides insights into the use of deep learning in highlighting public opinion on ongoing issues.

2. Literature Review

2.1. Sentiment Analysis

Sentiment analysis is a technique in Natural Language Processing (NLP) used to identify, extract and classify the sentiment in a text as positive, negative, or neutral (Liu, 2012). This analysis is often done in many fields such as public opinion, product reviews, and others, the goal is to know the public's response to a topic. Sentiment analysis helps in identifying the public's response to current issues without the need to collect data manually through surveys or interviews, so it can get a large amount of data analysis and save time.

User-generated comments on stages such as YouTube serve as an important reflection of open supposition with respect to the issues displayed in transferred recordings. As a wealthy source of subjective information, these comments give analysts a compelling means to investigate open opinion over a wide range of points. The enormous volume and differing qualities of reactions upgrade the profundity and breadth of assumption examination, empowering a more nuanced understanding of group of onlookers responses. By applying assumption examination methods, analysts can reveal passionate patterns, track shifts in open discernment, and recognize designs in group of onlookers reactions over time. These experiences are especially useful for substance makers, organizations, and researchers, advertising convenient and exact criticism on how a point or video is gotten. Besides, assumption examination of YouTube comments can play a significant part in notoriety checking, early discovery of rising issues, and supporting real-time, data-informed decision-making forms.

2.2. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a network developed to address issues commonly found in Recurrent Neural Networks (RNNs), particularly the vanishing gradient problem when processing large-scale data. LSTM is structured to enable the model to maintain information across extended time intervals. It is effective because of its ability to handle complex dependencies in text, such as relationships between interdependent words (Hochreiter & Schmidhuber, 1997).

Previous studies have shown that LSTM outperforms other models in dealing with sequential data like text, as it can preserve temporal relevance without losing contextual meaning (Hochreiter & Schmidhuber, 1997). These studies also indicate that LSTM achieves higher accuracy than other methods, such as Naïve Bayes and Support Vector Machines, in analysing public sentiment.

2.3. Public Opinion

Public opinion refers to the views held by society regarding issues circulating within the public sphere. The formation of public opinion is influenced by various factors such as mass media, social environment, and others. In the digital era, social media has become the most extensive space and a primary platform for the public to freely express their opinions on various topics. Previous research has shown that social media plays a significant role in shaping and reflecting public opinion, particularly on political issues (McGregor & Mourão, 2016).

Public opinion is constantly changing and influenced by many different things, not just the media. The people around us like family, friends, coworkers, and community members play a big part in shaping what we think, as we often find ourselves agreeing with those close to us. Our feelings and mental shortcuts, such as biases or emotions like fear and empathy, also affect how we form and share our opinions. Influential figures like celebrities, politicians, and thought leaders can have a strong impact by sharing their views and inspiring others. Moreover, the way we learn about politics and society through family, school, and peers helps shape our beliefs over time. All these factors work together to create a lively and ever-changing mix of public opinions that influence the decisions made in our communities and beyond.

3. Materials and Methods

3.1. Materials

This study focuses on public opinion regarding Donald Trump's policy on the increase of global tariffs. The research sample consists of user comments collected from a YouTube video titled “Trump Unveils Sweeping Global Tariffs in Watershed Moment for World Trade”, published by BBC News on April 3, 2025. A total of 3,543 comments were gathered as the dataset for this analysis. The data collected includes the username, date, number of likes, and the content of each comment. Sentiment analysis is conducted using the Long Short-Term Memory (LSTM) method to evaluate public reactions. The programming language used for this analysis is Python.

3.2. Methods

3.2.1. Data Collecting

The data in this study was collected from user comments on the YouTube video titled "Trump Unveils Sweeping Global Tariffs in Watershed Moment for World Trade", published by the BBC News channel. The information gathered includes the username, date of the comment, number of likes received, and the content of the comment.

3.2.2. Preprocessing Data

Before the analysis is conducted, the collected data undergoes a preprocessing stage to clean the data. The steps involved are as follows (Nurfebia & Sriani, 2024):

(1) Case Folding is the process converts all text into lowercase characters, while also eliminating punctuation and numerical symbols to standardize textual input for further analysis.
(2) Cleaning is the process of removing irrelevant characters in the analysis, such as URLs, usernames, punctuation marks, numbers, and emoticons.
(3) Stopword Removal is the process of trimming additional vocabulary to eliminate less informative terms, including the removal of common words or slang.
(4) Stemming is the process to reduces inflected or derived words to their root forms by eliminating affixes, thereby simplifying word variations into their base forms.
(5) Tokenization is the process of breaking down a series of words in a text whether in the form of sentences, paragraphs, or an entire document into smaller parts such as individual words or phrases

3.2.3. Sentiment Analysis

Long Short-Term Memory analysis is the process of evaluating text by classifying it as positive or negative. This method is also referred to as opinion mining, as it aims to identify perspectives or opinions about a given subject. A common application of this analysis is understanding public comments about a product (Balusamy et al., 2021). By examining the language used in these opinions, the analysis can also uncover the reasons behind people's preferences or dislikes toward a product.

3.2.4. Long short-Term Memory

Long Short-Term Memory (LSTM) is used in this study to analyze the sentiment of the collected comments. LSTM is an extension of Recurrent Neural Network (RNN) designed to capture long-term dependencies in sequential data, making it highly effective for text-based sentiment analysis. The application of LSTM in sentiment analysis involves several steps (Zhang et al., 2018):

(1) Word Embedding: The text data is converted into vector representations using techniques such as Word2Vec or GloVe.
(2) Training the LSTM Model: The LSTM model is trained using a labeled dataset (if available) or pre-trained embeddings. The model is trained to recognize patterns within the text to determine whether the expressed sentiment is positive, negative, or neutral.
(3) Model Evaluation: The model's performance is assessed using metrics such as accuracy, precision, recall, and F1-score to determine its effectiveness in sentiment classification.

3.2.5. Classification and Sentiment Labeling

After the training process, the LSTM model is applied to determine the sentiment of each comment. These comments are then assigned sentiment labels as follows:

(1) Positive: Indicating supportive or favorable viewpoints.
(2) Negative: Reflecting criticism or unfavorable opinions.
(3) Neutral: Representing a lack of strong positive or negative emotion.

3.3. Structure

This study is a quantitative type of research, even though the object being analysed is in the form of text data. This is because, in sentiment analysis, the data is transformed into numerical form and analysed statistically using the LSTM method. The type of data used is secondary data obtained from YouTube comments. The data collected for analysis includes the username, date, number of likes, and the content of the comment.

3.4. Formula / Equation

In sentiment analysis using the Long Short-Term Memory (LSTM) method, the model learns the contextual relationships and word sequences within the text to classify sentiment as either positive or negative. LSTM has a basic structure consisting of three main gates (Hochreiter & Schmidhuber, 1997).

Forget Gate

This gate finds information that must be discarded from the memory cell.

$$f_t = \sigma(W_f . [h_{t-1}, x_t] + b_f \tag{1}$$

Input Gate

This gate determines what new information will be added to the memory cell.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C} = \tanh(W_c . [h_{t-1}, x_t] + b_C)$$

Cell State Update

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{3}$$

Output Gate

$$o_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \tag{4}$$

$$h_t = o_t * \tanh(C_t)$$

Where:

x_t : the current input (text features that have been embedded),
h_t : the current hidden state,
C_t : the cell state,
σ : the sigmoid activation function,
$tanh$: the tanh activation function,
W : weights
b : biases

3.5. Flow Chart

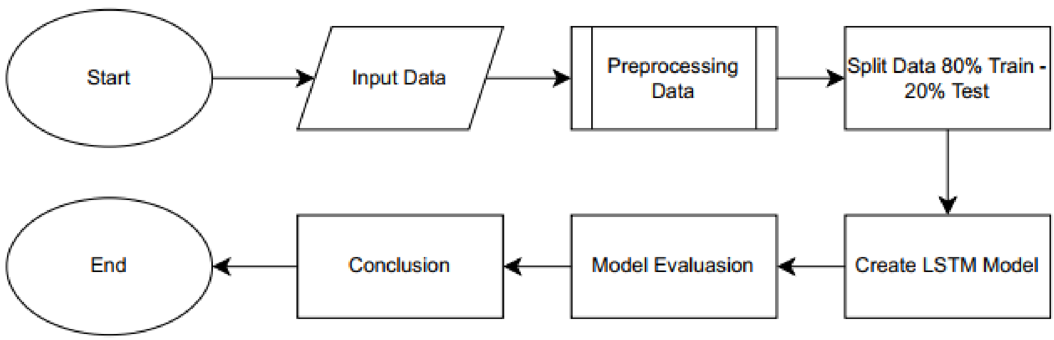

Figure 1: Research Flow Diagram

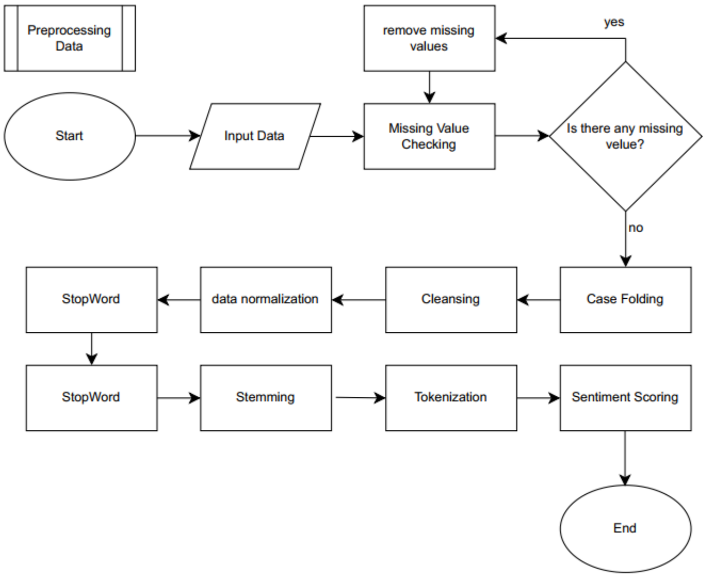

Figure 2: Preprocessing Data Flow Diagram

4. Results and Discussion

The data was obtained through comments on the BBC News YouTube channel with the title “Trump Unveils Sweeping Global Tariffs in Watershed Moment for World Trade,” uploaded on April 3, 2025. The data was analysed using the Python programming language on the Google Collab website. Python was used to process the data collected from the YouTube comment section, which consisted of 3,543 comments. Preprocessing was then performed to make the data more effective for the analysis algorithm model. The data was split into 80% training data and 20% testing data to train the LSTM model that would be built, resulting in the Classification Report shown in Figure 3.

23/23 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step

	precision	recall	f1-score	support
Negative	0.77	0.84	0.81	418
Positive	0.74	0.64	0.69	291
accuracy			0.76	709
macro avg	0.76	0.74	0.75	709
weighted avg	0.76	0.76	0.76	709

Figure 3: Classification Matrix

The performance of this LSTM method gives a performance of 76% Accuracy with 77% precision, 84% recall, and 81% f1-score on negative sentiment and 74% precision, 64% recall, and 69% f1-score on positive sentiment. Conclussion. In Figure 4, the evaluation of the LSTM model's accuracy is presented.

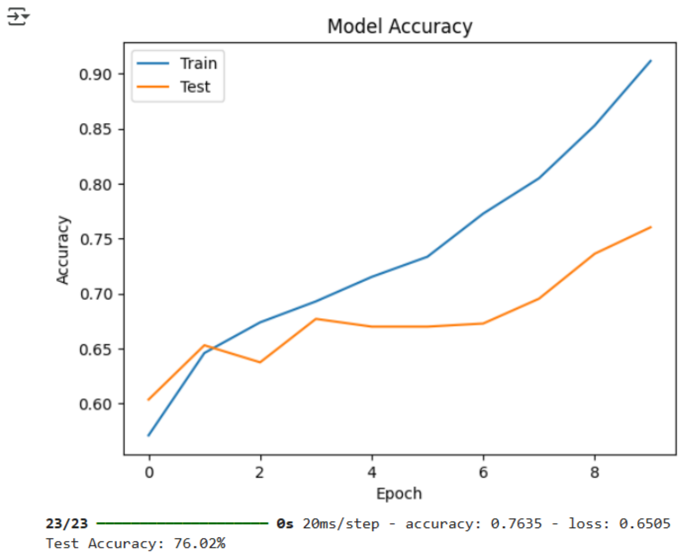

Figure 4: Model Accuracy

The final model accuracy on the test data is 76.02%, with a training accuracy of 76.35% (0.7635) in the last epoch and a loss value of 0.6505. Given that the training and test accuracy are very close, it can be inferred that no significant overfitting occurred. In Figure 5, the sentiment analysis results are presented in a pie chart.

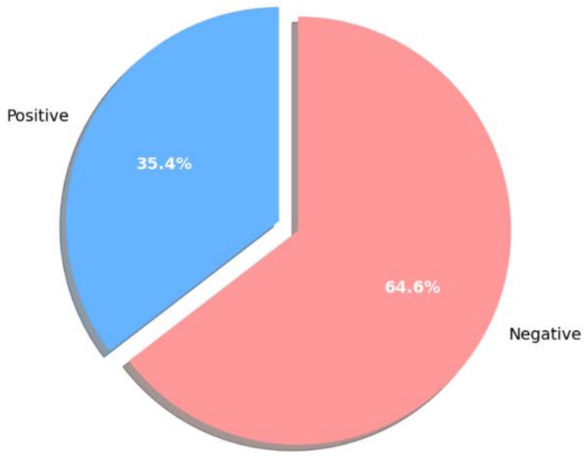

Figure 5: Sentiment Analysis

In conclusion, the analysis of public feedback on the policy reveals a significant imbalance, with negative sentiment dominating at 64.6% compared to positive sentiment at 35.4%. This disparity signals strong public dissatisfaction and underscores the urgency for policy reevaluation.

5. Conclusion

The results of sentiment analysis using the Long Short-Term Memory (LSTM) method indicate that public sentiment leans more toward the negative. This suggests that many users disagree with President Donald Trump's statement regarding the global tariff announcement implemented by the United States government. This sentiment negative is visually represented in the word cloud shown in Figure 6.

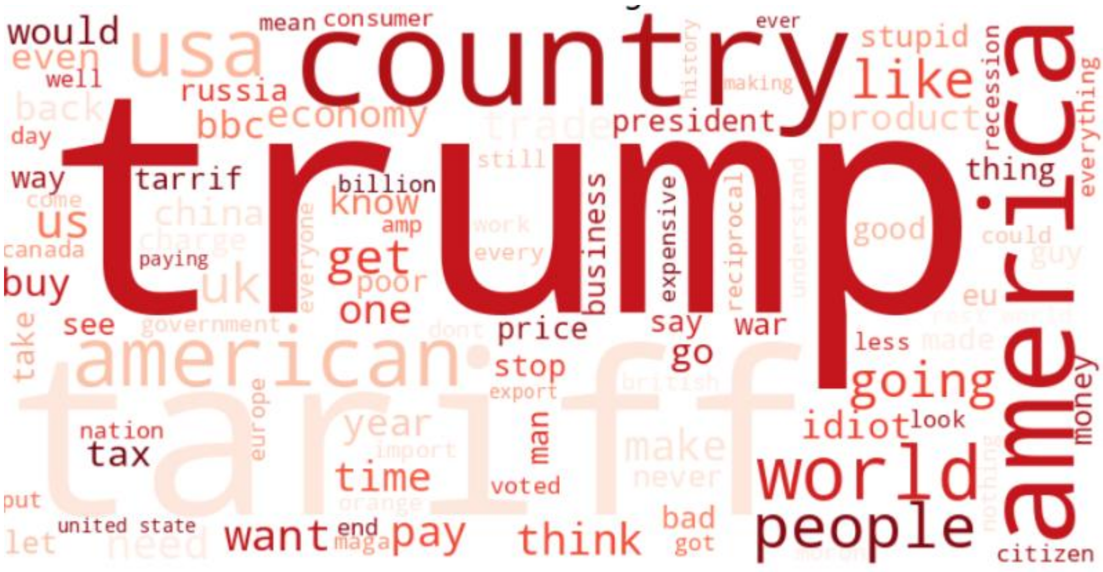

Figure 6: Word Cloud For Negative Sentiment

Words that appear in larger font sizes in the word cloud indicate higher frequency of occurrence in the comments, particularly those associated with negative sentiment. From the word cloud, it can be observed that the most frequently mentioned words in the negative sentiment category are *"Trump"* and *"Tariff"*.

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