Classification Model for Sentiment analysis of 2020 US Election Tweets

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***Abstract*— This research paper investigates the correlation between social media trends during the 2020 US presidential election and public sentiment towards candidates Donald Trump and Joe Biden across the United States of America. Utilizing sentiment analysis of tweets, the study aims to uncover insights into the impact of political discourse on public opinion. Key research questions include the extent to which social media trends reflect public sentiment towards the candidates and the factors influencing sentiment polarity. By analyzing 4.1 million sentiments expressed in tweets, the study provides valuable insights into the dynamics of public opinion during a significant political event. The research employs exploratory data analysis (EDA), data preprocessing, and machine learning algorithms to analyze Twitter data related to the election. Findings reveal that Donald Trump emerged as the most talked-about candidate globally, with a higher overall tweet count. However, sentiment analysis indicates a larger portion of positive tweets towards Joe Biden, aligning with the broader election results. The study highlights the scalability and applicability of sentiment analysis techniques in understanding public opinion dynamics and shaping political discourse.**

Keywords*— *social media, sentiment analysis, twitter, 2020 US presidential election, public opinion, Apache Spark, distributed computing, machine learning

I. Introduction

Today's society cannot be understood without the role of social media. Online users connect more and more via platforms that enable content sharing, either generic or around specific topics, and do this by means of text-only messages, or augmenting them with multimedia content such as pictures, audio or video.

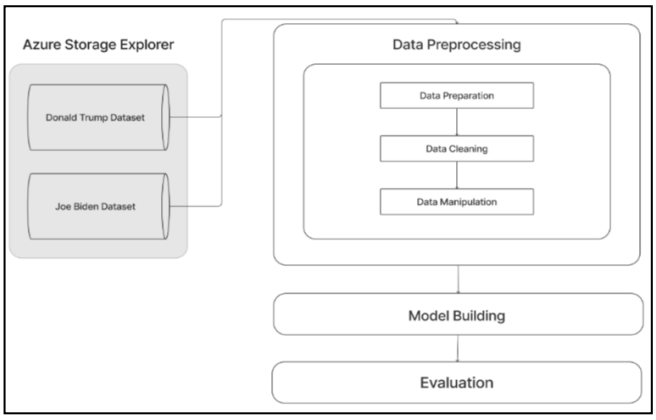
In today's world, social media sites like Twitter are commonplace and allow people to instantly express their thoughts, feelings, and opinions on a variety of subjects. The massive volume of data generated on these platforms presents a valuable opportunity for sentiment analysis, which aims to classify textual data into positive, negative, or neutral sentiment polarities. Twitter's instantaneous communication can occasionally become a centre of controversy and false information, particularly when it comes to political matters. Every democracy starts with free and fair elections. Among the most significant and divisive of these events was undoubtedly the 2020 US presidential election. Two-thirds of the voting-eligible population voted, resulting in the highest turnout in the past 120 years (Schaul, Rabinowitz, and Mellnik 2020). One particularly relevant application of sentiment analysis is understanding public opinion and sentiment towards major events or issues. The 2020 US presidential election, for instance, generated a deluge of tweets expressing diverse viewpoints and emotions. Analysing the sentiment of these tweets can provide insights into the public's perception of the candidates, campaigns, and election results [1] [2] [3] [4]

Current literature on Sentiment Analysis struggle with the noisy and informal nature of text on social media platforms like Twitter. Tweets often contain abbreviations, slang, misspellings, and unconventional grammar, which can pose challenges for traditional natural language processing techniques. Addressing this limitation is crucial for developing robust models tailored for social media data. [5]

Many sentiment analysis models are trained on datasets that may contain biases, such as demographic or ideological skews. This can lead to unfair or inaccurate sentiment classifications for certain groups or topics. Addressing these biases and ensuring fairness in sentiment analysis models is an ongoing challenge. [6]

This research aims to develop and evaluate a robust classification model for sentiment analysis of tweets, with a particular focus on the 2020 US presidential election for both candidates Donald Trump and Joe Biden. By analysing the 4.1 million sentiments expressed in tweets, this research seeks to uncover potential correlations between public opinion on social media and real-world events or outcomes, such as election results in our case.

II. Project Lifecycle



III. PROPOSED METHODOLOGY

A. Exploratory Data Analysis

Exploring data is vital when dealing with big datasets. It helps uncover patterns and insights crucial for understanding the complexities of big data. We conducted Exploratory Data Analysis (EDA) to gain insights into the Twitter data related to the 2020 US presidential election. Initially, we visualized the distribution of tweet counts across different countries using a choropleth map, highlighting regions with the highest engagement. Subsequently, we employed horizontal bar charts to identify the top five countries contributing to tweet volumes, providing a clear comparison of global engagement levels. To further delve into regional sentiments, we utilized bar charts to showcase the top five US states with the highest tweet counts, shedding light on domestic discourse. Additionally, we explored the distribution of tweet sources for each candidate, represented in a pie chart, offering valuable insights into user engagement preferences. This comprehensive EDA facilitated a nuanced understanding of online conversations surrounding the election, laying the groundwork for subsequent analysis and interpretation.

B. Data Preprocessing

In our research's data preprocessing phase, we took several steps to prepare the Twitter dataset for sentiment analysis.

1) Data Preparation:

First, we created a 'hashtag' column to indicate whether each tweet was about Joe Biden or Donald Trump. Tweets related to Trump were labeled 'Trump', and those about Biden were labeled 'Biden'. Then, we combined the separate data frames for Biden and Trump tweets into one for unified analysis. We focused solely on tweets from the United States by filtering the dataset to include only those labeled as 'United States of America' or 'United States'. This step was essential for our analysis, as it allowed us to examine public opinion within the US accurately. Finally, we streamlined the data by removing irrelevant features, ensuring that only essential features remained for sentiment analysis. This step was crucial in managing big data effectively, as it reduced the volume of information and eliminated unnecessary clutter, allowing for more efficient analysis.

2) Data Cleaning:

Data cleaning is crucial, especially when handling big data, as it ensures that the massive volume of information is accurate, consistent, and devoid of errors. By systematically removing irrelevant or misleading information, data cleaning enhances the reliability and quality of subsequent analyses, leading to more informed decision-making and insights extraction.

3) Text Cleaning:

In the data cleaning phase, we first cleaned the 'tweet' text by removing hashtags, usernames, URLs, emojis, and special characters. This process was carried out using a custom User Defined Function (UDF) along with regular expressions and the emoji library for efficient pattern matching and removal. This tailored approach ensured that the text was stripped of unnecessary elements, resulting in a column named 'tweet_cleaned' containing the refined text ready for analysis.

4) Tokenization:

Following text cleaning, we employed tokenization to break down the cleaned text into individual words. This was facilitated by the RegexTokenizer, a PySpark feature, which utilizes regular expressions to split text into tokens. By using the regular expression pattern '\W', non-word characters were ignored, ensuring that only meaningful words were retained for analysis. This step laid the foundation for further processing.

5) Stopwords Removal:

After tokenization, the next step was to remove common stop words from the tokenized text. This process was carried out using the StopWordsRemover stage to eliminate frequently occurring words such as 'the', 'is', and 'and', which carry little semantic meaning and may introduce noise into the analysis. Removing these words focused the analysis on the most relevant terms, thereby enhancing result accuracy and interpretability.

6) HashingTF:

In the final stage of the preprocessing pipeline, we transformed the cleaned and tokenized text into numerical feature vectors using the hashing trick, implemented through the HashingTF stage. This technique mapped each term in the text to a unique index in a fixed-size feature vector, facilitating dimensionality reduction and vectorization of textual data. Standardizing the input format improved the efficiency and scalability of subsequent modeling tasks.

C. Data Manipulation

Data manipulation serves as the cornerstone while handling vast amount of data, providing the foundation for accurate analysis and model building. In our project, we emphasised the importance of data manipulation by creating custom user-defined function rather than using existing MLlib libraries to encode categorical variables such as hashtags and sentiment labels. By tailoring the encoding process to our specific requirements, we ensured that the data was mapped properly and ready for model training. This meticulous approach to data manipulation not only facilitated smoother preprocessing but also laid the groundwork for more robust and accurate sentiment analysis.

To conclude, data preprocessing was crucial in this project to guarantee the accuracy and reliability of the sentiment analysis model. By systematically cleaning and structuring the tweet data, including removing irrelevant elements and standardising the text format, we enhanced the quality of the input data for subsequent steps. This preprocessing step facilitated more meaningful insights and improved the overall performance of the sentiment analysis model.

IV. EXPERIMENTAL SET-UP

In this section, we outline the experimental setup devised to evaluate the performance of various machine learning (ML) models employed in sentiment analysis tasks. The experimentation aims to assess the effectiveness of different ML algorithms in predicting sentiment polarity

based on Twitter data pertaining to the 2020 US presidential election. The experimental setup forms the foundation for evaluating the efficacy and generalization capabilities of the alternative ML models in sentiment analysis.

We utilized the VectorAssembler from PySpark's ML feature module to assemble independent features, including the textual features and the encoded hashtag information, into a single feature vector named "Independent Features". This step facilitates the integration of multiple features into a format suitable for machine learning model training and evaluation.

A. Logistic Regression

Logistic Regression is a supervised learning technique commonly used for classification tasks, where the goal is to predict the probability that an instance belongs to a particular class. The logistic function, also known as the sigmoid function which, transforms any real-valued input into a value between 0 and 1, representing the probability of the positive class. The sigmoid function ensures that the output of the logistic regression model remains within the valid probability range, facilitating the interpretation of the model's predictions.

The mathematical equation for the logistic function is as follows:

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

where,

$\sigma(z)$ represents the logistic function.

z is the linear combination of feature values and corresponding coefficients.

In our study, we used logistic regression as a key tool for sentiment analysis. We trained a model using filtered Twitter data related to the 2020 US presidential election. We made sure to exclude any data points with labels outside the valid range to ensure accurate training. By analysing the features extracted from the tweets and their corresponding sentiment labels, the logistic regression algorithm learned to identify patterns. Through optimization, the model adjusted its parameters to improve accuracy. Ultimately, this logistic regression model provided valuable insights into sentiment trends across different sources of textual data.

B. Random Forest Classifier

Random Forest Classifier is a widely-used ensemble learning method for classification tasks, renowned for its robustness and versatility. It leverages a collection of decision trees to make predictions, with each tree trained on a random subset of the training data and features. The ensemble of decision trees is designed to collectively minimise classification error by combining the predictions of individual trees through a voting mechanism. Random Forest Classifier combines the strengths of decision trees with ensemble learning, resulting in a powerful algorithm capable of handling large datasets and high-dimensional feature spaces. It provides robustness against overfitting and estimates feature importance, enabling interpretation and feature selection.

In our research, this Random Forest Classifier constructs multiple decision trees using random subsets of the training data and features, and then aggregates their predictions to make robust and accurate classifications. By training a Random Forest model with decision trees on our filtered training dataset, we aimed to harness the collective predictive power of multiple trees to achieve superior classification performance. This approach offers advantages such as resilience to overfitting, ability to handle large datasets, and estimation of feature importance, making it well-suited for our sentiment analysis task.

C. Support Vector Machine

Support Vector Machine (SVM) is a powerful supervised learning algorithm commonly used for classification tasks, including sentiment analysis. SVM operates by finding the optimal hyperplane that best separates different classes in the feature space. The hyperplane is positioned to maximize the margin, which is the distance between the hyperplane and the nearest data points (support vectors) from each class. SVM is known for its ability to handle high-dimensional data and generalize well to unseen samples, making it suitable for sentiment analysis tasks where feature vectors represent textual information extracted from tweets.

Mathematically, the decision function of a linear SVM can be represented as:

$$f(x)=w\cdot x+bf(x)=w\cdot x+b$$

where,

$f(x)$ is the decision function that predicts the class label of the input vector xx.

w is the weight vector perpendicular to the hyperplane.

b is the bias term that shifts the hyperplane away from the origin.

In our research, the LinearSVC classifier was trained on the preprocessed dataset, utilizing features generated through vectorization and encoding. The model was evaluated using the BinaryClassificationEvaluator. The obtained accuracy of the LinearSVC model provides valuable insights into its effectiveness in predicting sentiment polarity from tweet data, contributing to the broader assessment of machine learning algorithms in sentiment analysis tasks.

V. Result and Discussion

In this section, we present the main findings of our research on sentiment analysis of tweets related to the 2020 US presidential election, focusing on the candidates Donald Trump and Joe Biden. We interpret the results and discuss their significance, highlighting the capabilities and implications of our proposed solution.

A. Exploratory Data Analysis:

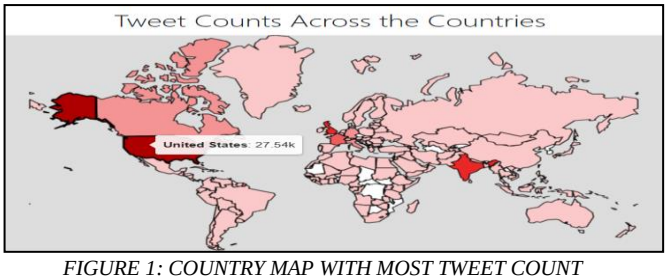
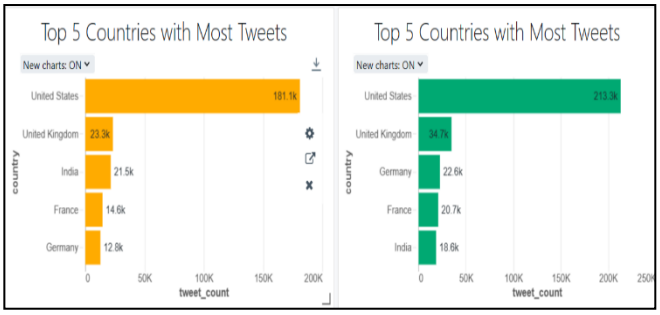


FIGURE 1: COUNTRY MAP WITH MOST TWEET COUNT

By visualizing the feature ‘country’ in our dataset we analyzed those top countries with the greatest number of tweets for the US election 2020 are USA, UK, India, France, Germany, Canada. The visualization in Figure 1 clearly indicates that the USA leads the tweet count table with 27.54k tweets.

We further dissected our analyses by visualizing Top 5 countries with Tweets for Joe Biden and Donald Trump as shown in Figure 2.



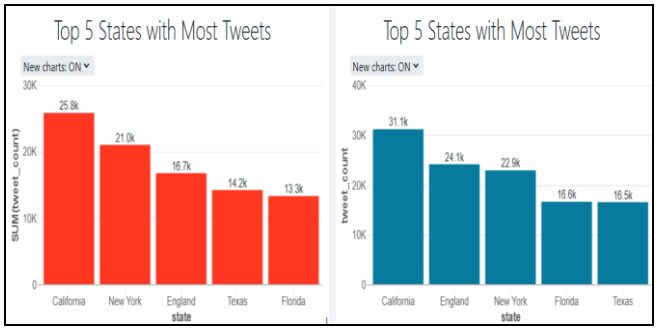
JOE BIDEN DONALD TRUMP

FIGURE 2: TOP 5 COUNTRIES WITH TWEET COUNTS FOR JOE BIDEN AND DONALD TRUMP

From the analysis of tweets from the top 5 countries, it's evident that Donald Trump leads in overall tweet count with 309K tweets, surpassing Joe Biden who has 253K tweets. This observation highlights Donald Trump as the most talked-about US presidential candidate across the globe.

From both the above analysis presented in Figure 1 & 2 it is very evident that tweets count from USA significantly dominates when compared to other nations.

Therefore, in the analysis presented in Figure 3 we check the top 5 USA states with the most tweet count for individual candidates.

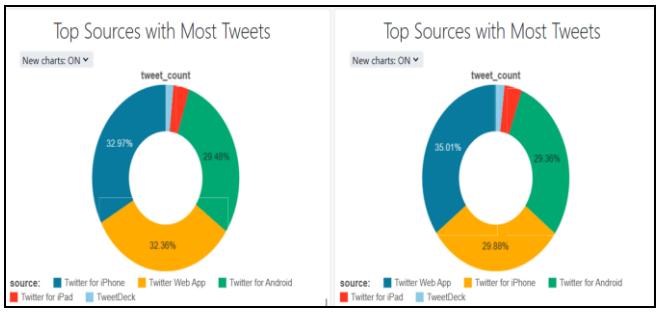


JOE BIDEN DONALD TRUMP

FIGURE 3: TOP 5 USA STATES WITH TWEET COUNTS FOR JOE BIDEN AND DONALD TRUMP

Our analysis illustrated USA states California, New York, New England, Florida, Texas to be the top 5 states that exhibited a higher number of tweets for Donald Trump compared to Joe Biden, emphasizing Donald Trump's prominence in online discussions across various regions.

We also visually analyzed the feature ‘source’ in our dataset. This feature contains information about the type of mobile device used, its operating system and web application were used to tweet for both the candidates as displayed in Figure 4.



JOE BIDEN *DONALD TRUMP*

FIGURE 4: TYPE OF SOURCE TO TWEET FOR JOE BIDEN AND DONALD TRUMP

The analysis in Figure 4 shows many tweets coming from both mobile and web platforms for both candidates. The Twitter Web App seems to be favored by users, indicating a preference for tweeting from computers. Also, tweets from mobile devices, especially iPhones and Androids, suggest active participation in political discussions on the move. These insights into tweet sources offer valuable demographic and behavioral data, useful for shaping campaign strategies and understanding user preferences and engagement patterns.

Our study of Twitter data from the 2020 US presidential election revealed key insights into online discussions about Joe Biden and Donald Trump. By analyzing tweet counts, likes, and sources across various regions, we observed Donald Trump's prominence in online conversations, indicated by his higher tweet count. Understanding tweet sources provided valuable insights into user preferences and behaviours. Our findings lay the groundwork for deeper exploration of sentiment trends and public opinion during the election.

B. Model Performance Evaluation

To evaluate the performance of our sentiment analysis models, we employed several evaluation metrics commonly used in classification tasks. Table 1 summarizes the accuracy scores achieved by the three models: Logistic Regression, Random Forest Classifier, and Support Vector Machine (SVM) Classifier.

Model	Accuracy
Logistic Regression	85.34%
Random Forest	61.22%
Support Vector Machine Classifier	87.48%

TABLE 1: MODEL PERFORMANCE ON SENTIMENT ANALYSIS TASK

Logistic Regression, with an accuracy of 85.34%, also demonstrated competitive performance, showcasing its effectiveness in modeling the relationship between the textual features extracted from tweets and their corresponding sentiment labels.

Interestingly, the Random Forest Classifier exhibited a relatively lower accuracy of 61.22%. This could be due to the inherent complexity of the sentiment analysis task and the potential presence of noise or ambiguity in the textual data, which may have hindered the performance of the ensemble decision trees.

The SVM Classifier achieved the highest accuracy of 87.48%, outperforming the Logistic Regression and Random Forest Classifier models. The strong performance of the SVM Classifier can be attributed to its ability to

handle high-dimensional feature spaces and its robustness to outliers and noise, which are common characteristics of social media data.

C. Sentiment Analysis Insights

Our sentiment analysis pipeline, which included preprocessing, feature engineering, and model training, provided valuable insights into the public sentiment surrounding the 2020 US presidential election. Table 2 presents a visualization of the sentiment distribution across the two candidates, Donald Trump and Joe Biden, based on the predictions of our best-performing model, the SVM Classifier.

Presidential Candidate	**Positive Tweet Count**	**Negative Tweet Count**
Donald Trump	77336	135927
Joe Biden	75512	105625

TABLE 2: SENTIMENT DISTRIBUTION FOR DONALD TRUMP AND JOE BIDEN

As depicted in the table 2, a larger portion of tweets expressed a positive sentiment towards Joe Biden compared to Donald Trump. This observation aligns with the overall election results, where Joe Biden emerged as the winner, suggesting that public sentiment on social media platforms like Twitter may have reflected the broader public opinion during the election period.

However, it is important to note that our analysis focused specifically on Twitter data, which may not fully represent the sentiment of the entire voting population. Additionally, the sentiment expressed on social media platforms can be influenced by various factors, such as user demographics, political leanings, and potential biases within online communities.

D. Scaling-up Capabilities and Implications

One of the key strengths of our proposed solution lies in its scalability and ability to handle large-scale datasets. By leveraging distributed computing frameworks like PySpark, our data preprocessing and feature engineering pipelines can be parallelized and executed across multiple nodes, enabling efficient processing of massive volumes of data.

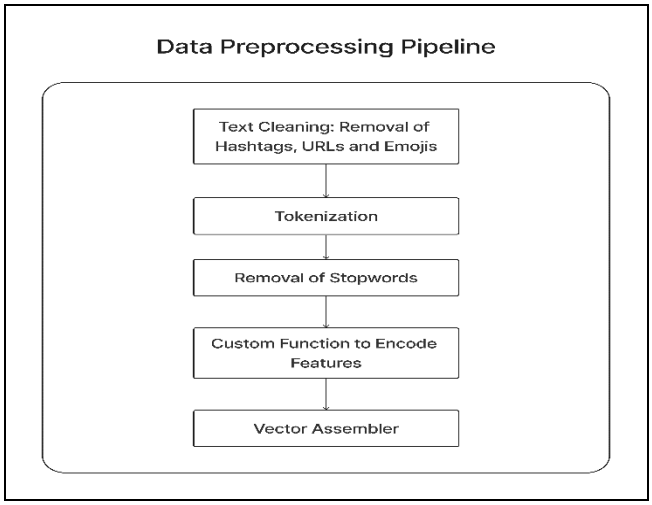


FIGURE 6: SCALING-UP CAPABILITIES OF THE PROPOSED SOLUTION BY IMPLEMENTING PREPROCESSING PIPELINE.

The data preprocessing pipeline, shown in Figure 6, serves as a basis of our solution, facilitating efficient and scalable processing of vast social media datasets. Its modular design enables easy modification, replacement, or extension of specific stages, ensuring flexibility and adaptability to evolving data sources and preprocessing techniques. Leveraging distributed computing frameworks like PySpark, the pipeline achieves scalability by parallelizing processing tasks across multiple nodes or clusters, enabling real-time sentiment analysis on extensive datasets. Moreover, the pipeline promotes reproducibility and consistency in preprocessing steps, ensuring reliable sentiment analysis results across different datasets and analysis runs. Overall, its structured, scalable, and flexible nature makes it well-suited for handling the complexities of social media data and supporting dynamic requirements and user behaviors.

E. Discussions

Our research demonstrates the potential of sentiment analysis techniques in understanding public opinion and sentiment dynamics surrounding major events like the 2020 US presidential election. By leveraging machine learning algorithms and preprocessing techniques tailored for social media data, we were able to extract valuable insights from the vast amount of Twitter data generated during the election period.

The findings of our study have several implications:

1. Campaign Strategy and Communication: The ability to analyze public sentiment on social media platforms can inform political campaigns and communication strategies. By understanding the sentiment towards candidates and their policies, campaigns can tailor their messaging, address concerns, and engage with supporters more effectively.

2. Public Opinion Monitoring: Our solution enables continuous monitoring of public opinion and sentiment trends, providing valuable insights for policymakers, advocacy groups, and media organizations. This information can help shape public discourse, address misinformation, and foster more informed decision-making processes.

3. Early Warning System: Sentiment analysis on social media data can serve as an early warning system for detecting potential issues or controversies. By identifying sudden shifts in sentiment or emerging negative sentiment patterns, appropriate measures can be taken to address concerns and mitigate potential impacts.

4. Targeted Messaging and Outreach: By analyzing sentiment patterns across different demographic groups or geographic regions, targeted messaging and outreach efforts can be developed to address specific concerns or engage with diverse communities more effectively.

While our research focused on the 2020 US presidential election, the methodologies and techniques employed can be extended to analyze sentiment dynamics surrounding various other events, issues, or domains, making our solution widely applicable and adaptable.

VI. Conclusion

This research employed sentiment analysis techniques to gain insights into public sentiment surrounding the 2020 US presidential election candidates, Donald Trump, and Joe Biden, from Twitter data. We preprocessed the data, engineered features, and evaluated multiple machine learning algorithms for sentiment classification. The Support Vector Machine (SVM) Classifier performed best, achieving 87.48% accuracy.

The analysis revealed larger positive sentiment towards Joe Biden compared to Donald Trump, aligning with the election results. However, limitations and biases exist in sentiment analysis of social media data, such as user demographics, political leanings, echo chambers, noise, sarcasm, and ambiguity.

The implications of this research are far-reaching. It can inform political campaigns, communication strategies, continuous public opinion monitoring, early warning systems for potential issues, and targeted messaging for diverse communities.

Future research should focus on addressing limitations by handling sarcasm, irony, ambiguity, incorporating multimodal data, exploring transfer learning and domain adaptation, and developing interpretable and explainable sentiment analysis models.

Overall, this study demonstrates the potential of sentiment analysis in understanding public opinion and sentiment dynamics during major events like elections. However, continued research is needed to overcome limitations and biases, fostering more accurate insights, informed decision-making, and inclusive democratic discourse.

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