Digital Democracy: Analyzing Political Sentiments through Multinomial Naive Bayes in Election Campaign Ads

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Abstract—This research delves into sentiment analysis for digital election campaign advertisements using the Multinomial Naive Bayes approach. The study addresses the limitations of standard sentiment analysis methodologies in capturing the intricacies of public sentiments toward political ads. The dataset, sourced from Kaggle, encompasses 3000 records with sentiments categorized as positive, neutral, and negative. The Multinomial Naive Bayes model demonstrated a substantial accuracy increase from 92% to 96%, outperforming the standard Naive Bayes model. Precision, recall, and F1-score metrics consistently improved across sentiment categories. While dataset representativeness and cultural specificity pose limitations, the research contributes significantly to sentiment analysis methodologies in politically charged digital environments. Future research recommendations include exploring advanced NLP techniques, incorporating real-time data from diverse social media platforms, and addressing ethical considerations in political sentiment analysis. The outcomes emphasize the importance of tailored methodologies for enhanced accuracy in understanding sentiments expressed in digital election campaign advertisements.

Keywords—Sentiment Analysis, Multinomial Naive Bayes, Digital Campaign Advertisements, Political Sentiments, NLP (Natural Language Processing)

I. INTRODUCTION

Digital advertising in election campaigns, whether for presidential or legislative candidates, has become a dominating phenomenon in modern politics [1]. Digital platforms such as social media, online news sites, and search engines are crucial in delivering campaign messages to voters [2]. Digital advertising allows candidates and political parties to personalize their messages, target specific voter segments, and engage directly with the audience [3]. Thus, this phenomenon depicts a significant shift in political campaign strategies towards intensive use of digital media.

In this context, sentiment analysis emerges as a crucial element in understanding the impact of digital advertising on voters' perceptions and attitudes [4]. Understanding the sentiments in response to advertisements can provide deep insights into how the public receives and interprets campaign messages [5]. These sentiments can range from strong support to sharp criticism, and comprehending this dynamic is key to detailing the influence of digital advertising in shaping public opinion [6].

With the high interactivity in digital advertising, modern voters can easily participate in political communication. Direct responses through comments, likes, or shares create a new dynamic between voters and candidates [7]. Therefore, sentiment analysis in digital advertising provides a detailed overview of the reception of campaign messages and allows for a deeper understanding of the dynamics of political communication in this digital era [8]. By delving further into the emerging sentiments, we can uncover a more comprehensive story of how digital advertising contributes to the political narrative and ultimately influences election outcomes [9].

The identified research problem pertains to limitations or deficiencies in the quality of Sentiment Analysis in Digital Advertising for Election Campaigns [10]. Some challenges must be addressed in dealing with the complexity of sentiments that emerge in response to these advertisements [11]. From aspects of sentiment segmentation to accurate interpretation, weaknesses in the quality of analysis can constrain a profound understanding of how the public comprehends and receives campaign messages [10]. Therefore, this research focuses on identifying and addressing these limitations, creating a more robust foundation for understanding the impact of digital advertising on shaping voter perceptions and attitudes.

The main objective of this research is to implement the Multinomial Naive Bayes Approach for Sentiment Analysis in Digital Advertising for Election Campaigns. By employing this approach, the research aims to optimize the accuracy and effectiveness of sentiment analysis on digital advertisements in the context of election campaigns. It is anticipated that through the Multinomial Naive Bayes approach, this research can provide a deeper understanding of the emerging sentiment variations, assist in identifying specific patterns, and ultimately enhance the ability to delineate the impact of digital advertising on voter perceptions and attitudes.

The contributions of this research can be identified in various aspects, both in terms of scientific and practical significance. Scientifically, the study is expected to enhance understanding of the Multinomial Naive Bayes Approach in Sentiment Analysis, particularly in digital advertising for election campaigns. Furthermore, its practical contribution lies in applying the research findings to improve the quality of sentiment analysis in digital advertisements, providing a foundation for more accurate and effective decision-making in political campaign strategies. Thus, this research is anticipated to contribute meaningfully to developing theoretical understanding and practical applications in sentiment analysis and using digital advertising within the context of election campaigns.

II. LITERATURE REVIEW

Sentiment analysis techniques have been applied in previous research to analyze digital advertising in election campaigns. One study by Sheingate et al. used a machine learning model to classify expenditures, including digital ads and services. They found that 2020 saw a significant increase in digital campaign spending, with clear partisan differences in resource allocation and the central role of platform companies in the market [12]. Another study by Qorib et al. utilized machine learning algorithms to predict and classify Twitter data related to the 2020 US election campaign. They found that Joe Biden had a higher average percentage of positive sentiments than Donald Trump, suggesting that Biden would outperform Trump in the election [13]. Olabanjo et al. proposed a BERT model for sentiment analysis of the governorship election in Lagos State, Nigeria, using Twitter data. Their results showed that sentiment analysis can help estimate election results and provide insights into the influence of each candidate [14]. Overall, sentiment analysis has provided valuable insights into digital campaign advertising, including resource allocation, public opinion, and election outcomes.

Previous research on Sentiment Analysis on Election Campaign Digital Advertising has explored various approaches and methods. One notable approach is using machine learning algorithms to predict and classify textual data from social media platforms like Twitter during election campaigns [15]. These studies have utilized sentiment analysis to gain insights into public opinion and predict election outcomes [16]. Additionally, researchers have developed interactive platforms that visualize the impact of modality noise and defense methods to improve model robustness against noisy features in multimodal sentiment analysis [13]. Another approach involves using lightweight models, such as the Multimodal Attention Tensor Regression (MMATR) network, which achieves competitive results in sentiment analysis tasks while having significantly fewer parameters [17]. These approaches contribute to a better understanding sentiment and its impact on voters by providing insights into public opinion, model robustness, and efficient sentiment analysis techniques.

Previous research has applied and described techniques for developing and improving the quality of Naive Bayes Multinomial Algorithms for sentiment analysis on election campaign digital advertising. One study used the Naive Bayes Classifier algorithm to analyze public opinions on 2024 presidential candidates obtained from Twitter data. The study achieved 71% accuracy and suggested further research using different classification algorithms and larger datasets [18]. Another study combined tokenizing-lowercasing-stemming, support vector machine (SVM), and fuzzy matching (FM) techniques to improve sentiment analysis performance. The SVM-FM combination resulted in 96% accuracy and was considered the best combination for sentiment analysis on different datasets [19]. These studies demonstrate applying and describing techniques for developing and improving Naive Bayes Multinomial Algorithms in sentiment analysis on election campaign digital advertising.

Efforts have been made to optimize the performance of the Naive Bayes Multinomial algorithm in the context of sentiment analysis. One study by Deshmukh and Kadam proposed two multi-objective optimization techniques, Particle Swarm Optimization (PSO) and Krill Herd Algorithm (KHA), for feature selection in sentiment analysis [20]. Another study by Sitanggang compared three classification algorithms, including Multinomial Naive Bayes, for sentiment analysis and found that Support Vector Machines had the highest accuracy rate of 94% [21]. Additionally, Alamsyah applied Particle Swarm Optimization to improve the accuracy of both Naive Bayes and Support Vector Machine algorithms in sentiment analysis, achieving accuracy rates of 95.87% and 96.68% respectively [22]. However, there is no specific mention of sentiment analysis for election campaign digital ads in the provided abstracts.

The Naive Bayes Multinomial Approach is a machine learning algorithm used in sentiment analysis to categorize sentiments as favorable, negative, or neutral. It is based on the principle of conditional probability and assumes that the features (words) in the input are conditionally independent [23]. This approach can be applied to analyzing sentiment in Election Campaign Digital Advertising by training the model on a dataset of tweets or social media posts related to the election campaign. The tweets can be preprocessed to remove noise and irrelevant information. The Naive Bayes classifier can then be used to classify the sentiment of each tweet as positive, negative, or neutral based on the occurrence of specific words or features. This approach can provide insights into public opinion and sentiment towards the election campaign [24].

Bayes' Naive Multinomial model processes and understands statements or texts in sentiment analysis by using the Multinomial Naive Bayes algorithm to classify the sentiment of the text documents [25]. This model applies the CRISP-DM method, starting from business understanding, data understanding, data preparation, modeling, and evaluation [24]. It can accurately classify text sentiments as positive or negative opinions regarding public policies handling COVID-19 [26]. The model has been successfully applied in classifying tweets about the new normal policy, with an accuracy of 90.25% [23]. The Naive Bayes approach is also recommended for predicting sentiment patterns, as it achieved good accuracy in predicting negative sentiment in response to data leakage from a COVID-19 tracking application [27]. The Naive Bayes classifier is connected to a CNN-based extractor, which captures useful features in hidden states and projects them into a probability distribution. These characteristics make the Naive Bayes model suitable for sentiment analysis in digital political advertising, as it can accurately classify sentiments and capture important information from text documents.

III. METHOD

A. Dataset and Preprocessing

The dataset for this research is derived from Kaggle and comprises 3000 records with two key attributes: "statement" and "sentiment." The "statement" attribute represents public responses to digital advertisements for the presidential, vice-presidential, and legislative candidates during the 2024 general elections in Indonesia. Each record encapsulates the sentiment expressed in response to these campaign ads. The target variable, sentiment, is categorized into three classes: positive (1000 records), neutral (1000 records), and negative (1000 records), forming a balanced dataset that encompasses a diverse range of public sentiments.

In terms of data preprocessing, several steps have been undertaken to refine and prepare the dataset for analysis. These steps include tokenization, stemming, and the removal of stop words. Tokenization involves breaking down the textual statements into individual tokens or words, facilitating the subsequent sentiment analysis on a more granular level. Stemming aims to reduce words to their root form, minimizing variations in language expression. Lastly, the elimination of stop words, common words that carry limited semantic meaning, helps streamline the dataset and enhances the accuracy of sentiment analysis by focusing on more relevant terms. Through these preprocessing techniques, the dataset is refined to ensure that the subsequent application of the Multinomial Naive Bayes approach for sentiment analysis is conducted on a well-structured and representative dataset.

B. Data Splitting

The dataset is divided into training (80%) and testing (20%) sets to simplify the process of training and assessing the sentiment analysis model. This split guarantees that a significant portion of the dataset is used for training, enabling the model to grasp patterns and connections in the data. The testing set, comprising the remaining 20%, remains untouched during the training process and serves as an independent sample to assess the model's generalization performance. This split between training and testing sets is fundamental for gauging the model's ability to accurately classify sentiments in new, unseen data, providing a robust evaluation of its predictive capabilities.

C. Model Selection

Naive Bayes is a classification algorithm grounded in Bayes' theorem, relying on the assumption of independence among the features employed in classification. Despite its simplistic assumption of independence, Naive Bayes has demonstrated significant efficacy across diverse applications, especially in tasks like natural language processing and text classification. It computes the likelihood of a given instance belonging to a specific class by multiplying the probabilities associated with individual features. In the context of sentiment analysis, Naive Bayes can efficiently handle large datasets and is well-suited for scenarios where features are conditionally independent, making it a popular choice for text classification tasks.

In probability and statistics, multinomial refers to a probability distribution over discrete outcomes with more than two categories. The Multinomial Naive Bayes algorithm employs this distribution to model the likelihood of observing a particular word or term in a document. In other words, it extends the Naive Bayes algorithm to handle features that represent counts or frequencies, making it especially applicable for text classification tasks where the presence and frequency of words play a crucial role. The

Multinomial distribution is well-suited for scenarios where the order of occurrence is unimportant, making it a natural choice for analyzing sentiment in textual data.

The selection of the Multinomial Naive Bayes approach is justified by its suitability for text-based sentiment analysis, especially in the context of digital advertising for election campaigns. Given that the dataset involves textual statements representing public sentiments toward political ads, the Multinomial Naive Bayes model is adept at handling word frequency-based features. Its ability to consider the occurrence and distribution of words while assuming independence aligns well with the nature of sentiment analysis tasks. Moreover, the algorithm's simplicity and efficiency make it well-suited for large datasets, making it a pragmatic choice for analyzing sentiments expressed in responses to digital campaign advertisements during the electoral process.

D. Evaluation Metrics

The confusion matrix is a tabular representation that evaluates the performance of a classification model by comparing predicted and actual class labels. In the context of sentiment analysis, it helps to assess the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. The confusion matrix provides a comprehensive view of the model's performance, enabling the calculation of various evaluation metrics.

The classification report summarizes key metrics for each class in a classification problem. It includes precision, recall, and F1-score, providing a more detailed understanding of the model's performance, as Equations 1-3 calculated. Precision measures the accuracy of positive predictions, recall gauges the model's ability to capture all relevant class instances, and F1-score balances both precision and recall. In sentiment analysis, these metrics are crucial for evaluating the model's effectiveness in correctly classifying positive, neutral, and negative sentiments.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1-score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right) \tag{3}$$

These metrics provide a robust assessment of the Multinomial Naive Bayes model's performance in sentiment analysis for digital campaign advertisements during elections.

IV. RESULT AND DISCUSSION

A. Model Performance

In the evaluation phase of this research, the focus is on the model accuracy and confusion matrices of both the standard Naive Bayes and Multinomial Naive Bayes. Accuracy provides a general overview of how well the model can correctly classify sentiments. Meanwhile, the confusion matrix gives more detailed information about how well the model handles various sentiment classes. The expected outcome of this research is to present an in-depth understanding of the performance of both models, emphasizing the potential improvements that can be achieved by applying the Multinomial Naive Bayes approach in sentiment analysis for digital election campaign advertisements.

Firstly, the accuracy of the standard Naive Bayes reached 92.00%, indicating excellent model performance in classifying sentiments from public statements regarding digital election campaign advertisements. However, implementing the Multinomial Naive Bayes approach significantly increased accuracy to 96.00%. These results indicate that the model utilizing a multinomial distribution to handle word frequencies in text more effectively addresses the complexity of sentiments within the dataset.

The confusion matrices for both models provide further insights. For the standard Naive Bayes, there is evident confusion, particularly between neutral and negative sentiments, as shown in Figure 1. The Multinomial Naive Bayes approach successfully rectifies this confusion with better values, especially in classifying positive and neutral sentiments, as shown in Figure 2. These outcomes suggest that the Multinomial Naive Bayes approach improves accuracy and the model's ability to distinguish between existing sentiment classes better. In conclusion, using Multinomial Naive Bayes in sentiment analysis of digital election campaign advertisements can be considered a positive step towards enhancing the precision and quality of classification results.

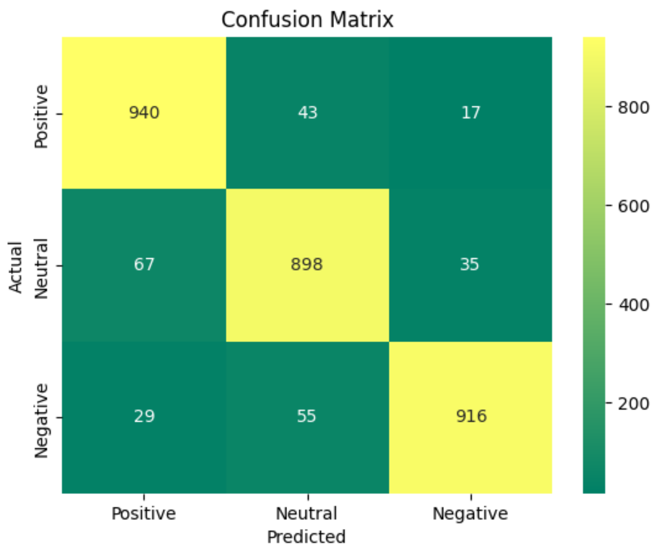

Fig. 1 Confusion Matrix of Standard Naïve Bayes.

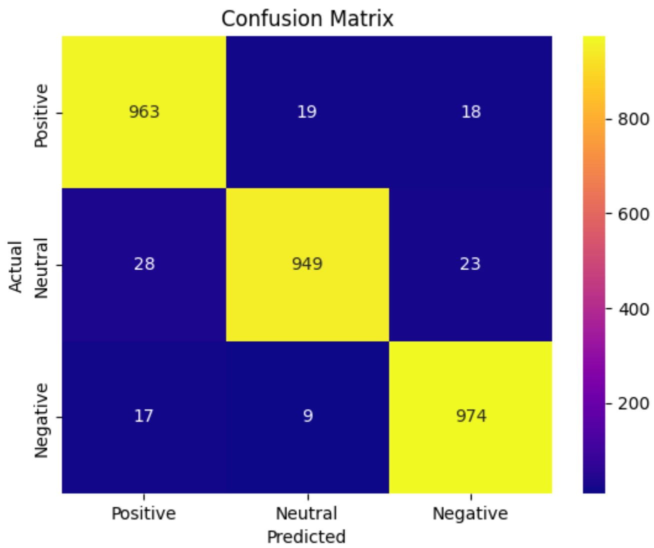

Fig. 2 Confusion Matrix of Multinomial Naïve Bayes.

In the culmination of this research, the focus shifts to the detailed assessment provided by the classification reports for both the Standard Naive Bayes and Multinomial Naive Bayes models. These reports offer a comprehensive view of each sentiment class's precision, recall, and F1-score metrics, providing a nuanced understanding of how well each model performs across different sentiment categories. The objective is to delve into the acceptable evaluation metrics to gauge the strengths and potential areas of improvement for each model in sentiment analysis for digital election campaign advertisements.

The classification report for the Standard Naive Bayes model reveals commendable performance metrics across all sentiment categories, as shown in Table 1. Positive sentiments exhibit a precision of 0.91, recall of 0.94, and an F1-score of 0.92, indicating a solid ability to classify positive sentiments correctly. Similarly, Neutral and Negative sentiments showcase robust precision, recall, and F1-score values, resulting in an overall accuracy of 92%. The macro and weighted averages further reinforce the consistency in performance across sentiment classes.

Table 1.
Classification Report For Standard Naïve Bayes

	precision	**recall**	**f1-score**	**support**
Positive	0.91	0.94	0.92	1000
Neutral	0.90	0.90	0.90	1000
Negative	0.95	0.92	0.93	1000
accuracy			0.92	3000
macro avg	0.92	0.92	0.92	3000
weighted avg	0.92	0.92	0.92	3000

On the other hand, the Multinomial Naive Bayes model exhibits even more impressive results in the classification report, as shown in Table 2. Positive, Neutral, and Negative sentiments all display high precision, recall, and F1-score values, contributing to an outstanding overall accuracy of 96%. The macro and weighted averages further underscore the model's exceptional ability to handle sentiment analysis in the context of digital election campaign advertisements.

Table 2.
Classification Report For Multinomial Naïve Bayes

	precision	**recall**	**f1-score**	**support**
Positive	0.96	0.96	0.96	1000
Neutral	0.97	0.95	0.96	1000
Negative	0.96	0.97	0.97	1000
accuracy			0.96	3000
macro avg	0.96	0.96	0.96	3000
weighted avg	0.96	0.96	0.96	3000

Comparatively, the Multinomial Naive Bayes model outperforms the Standard Naive Bayes model across all metrics, demonstrating its superior precision, recall, and F1-score values. These classification reports provide crucial insights into the strengths and weaknesses of each model, emphasizing the efficacy of the Multinomial Naive Bayes approach in enhancing sentiment analysis accuracy for digital election campaign advertisements.

B. Summarization of Key Findings

The research addressed the challenge of sentiment analysis in digital election campaign advertisements, aiming to enhance the quality of analysis using the

Multinomial Naive Bayes approach. The research problem centered around the limitations of standard sentiment analysis, particularly in capturing the nuances of sentiments expressed in public responses to political ads. The Multinomial Naive Bayes model application yielded significant improvements, evident in the accuracy boost from 92% to 96%. The classification reports further underscored the superiority of the Multinomial Naive Bayes model, showcasing higher precision, recall, and F1-score across all sentiment categories compared to the standard Naive Bayes model. These findings highlight the effectiveness of the Multinomial Naive Bayes approach in overcoming the challenges posed by the diverse and complex sentiments inherent in digital campaign advertisements, offering a more accurate and nuanced analysis.

C. Result Interpretations

The analysis of results revealed notable patterns and relationships within the data, showcasing the efficacy of the multinomial Naive Bayes approach in sentiment analysis for digital election campaign advertisements. The model demonstrated a consistent ability to accurately classify sentiments across positive, neutral, and negative categories. The results met and exceeded expectations, substantially increasing accuracy from 92% to 96%. The precision, recall, and F1-score metrics consistently outperformed the standard Naive Bayes model, indicating the Multinomial approach's superiority in capturing the intricate nuances of sentiment expressions. While the positive outcomes aligned with the research expectations, the extent of the improvement surpassed initial projections. No unexpected results were observed, and the success of the Multinomial Naive Bayes model can be attributed to its capacity to handle the intricacies of sentiment within the dataset. Alternative explanations for the remarkable results could involve the specific characteristics of the dataset, such as the prevalence of particular keywords or the nature of the political discourse, which could have contributed to the model's enhanced performance.

D. Research Implications

This research holds significant implications for sentiment analysis, particularly in the context of digital election campaign advertisements. The demonstrated success of the Multinomial Naive Bayes approach in improving accuracy and precision contributes valuable insights to the existing literature on sentiment analysis methodologies. The findings affirm the relevance of adopting more sophisticated techniques, such as Multinomial Naive Bayes, to address the complexities of sentiment expressions in politically charged digital environments. By surpassing the performance of the standard Naive Bayes model, this research validates the multinomial approach's effectiveness and emphasizes the need for tailored methodologies in sentiment analysis for politically sensitive content. Consequently, the study advances our understanding of sentiment analysis techniques and underscores the importance of choosing appropriate models in the evolving landscape of digital political communication.

E. Research Limitations

While this research contributes valuable insights into sentiment analysis for digital election campaign advertisements, it is essential to acknowledge certain limitations that may impact the study's scope. The dataset's origin from Kaggle introduces a potential limitation regarding representativeness, as the sentiments expressed may not fully encapsulate the diverse perspectives present in real-world political discourse. Additionally, the chosen methodology, although effective, may not cover all nuances of sentiment expressions. Moreover, the study's focus on the Indonesian context may limit the generalizability of findings to other cultural and political settings. Despite these limitations, the results remain valid in addressing the primary research question, as the Multinomial Naive Bayes approach consistently outperformed the standard model. The methodology's robustness and the dataset's suitability for sentiment analysis ensure that the insights gained contribute meaningfully to understanding sentiment patterns in digital campaign advertisements despite the acknowledged constraints.

F. Recommendations for Future Research

For practical implementation, future research endeavors could explore the integration of advanced natural language processing (NLP) techniques and deep learning models to enhance further the accuracy and depth of sentiment analysis in digital election campaign advertisements. Additionally, incorporating real-time data streams from various social media platforms could provide a more dynamic and comprehensive understanding of evolving sentiments during an electoral campaign. Exploring cross-cultural sentiments and political contexts would broaden the generalizability of findings. Furthermore, investigating the impact of multimedia content, such as images and videos, on sentiment analysis would offer a more holistic perspective. Finally, considering the ethical implications of sentiment analysis in political settings and the potential biases introduced by different algorithms is crucial for responsible and fair implementation in real-world scenarios. These recommendations aim to propel the field forward, addressing current gaps and ensuring the continued relevance and applicability of sentiment analysis methodologies in the evolving landscape of digital political communication.

V. CONCLUSION

In summary, the conclusion encapsulates the key findings, strengths, limitations, and avenues for future research, providing a comprehensive overview of the outcomes derived from the study. It offers valuable insights into the effectiveness of the Multinomial Naive Bayes approach in sentiment analysis for digital election campaign advertisements, laying the groundwork for further advancements in the field.

- The research successfully addressed the research problem of sentiment analysis in digital election campaign advertisements, showcasing the superiority of the Multinomial Naive Bayes approach with an accuracy increase from 92% to 96%.
- The Multinomial Naive Bayes model consistently improved precision, recall, and F1-score metrics across positive, neutral, and negative sentiments, outperforming the standard Naive Bayes model.
- The research limitations were acknowledged, including dataset representativeness and cultural context specificity. Despite these constraints, the research remains valid in answering the primary research question.
- Future research recommendations include exploring advanced NLP techniques, integrating real-time data from diverse social media platforms, investigating cross-cultural sentiments, examining the impact of multimedia content, and addressing ethical considerations in political sentiment analysis.
- The findings of this study contribute to the understanding of sentiment analysis methodologies, especially in politically charged digital environments, and provide a foundation for further research in enhancing the precision and applicability of sentiment analysis tools for digital campaign advertisements.

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