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Sentiment Analysis of Instagram Comments on the Ratification of the Criminal Procedure Code Bill using TF-IDF and Multinomial Naive Bayes

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ABSTRACT
The ratification of the Draft Criminal Procedure Code (RUU KUHAP) has generated significant public responses on social media platforms. This study aims to analyze public sentiment toward the ratification of the RUU KUHAP using Instagram user comments through sentiment analysis techniques based on Term Frequency–Inverse Document Frequency (TF-IDF) feature representation and the Multinomial Naive Bayes (MNB) classification algorithm. The data were collected using a web export method from relevant Instagram posts, followed by a comprehensive preprocessing stage, including text cleaning, tokenization, normalization, and stopword removal. The processed text was transformed into TF-IDF vectors and classified into three sentiment categories: positive, neutral, and negative. The experimental results show that the proposed model achieved an accuracy of approximately 66%, with the best performance observed in the negative sentiment class. The positive sentiment class was not effectively detected due to a highly imbalanced data distribution. Overall, the findings indicate that public sentiment toward the ratification of the RUU KUHAP is predominantly negative and neutral. This study provides empirical insights into public opinion on national legal issues and demonstrates the applicability of traditional machine learning approaches for sentiment analysis of short and informal social media texts.

Keywords: RUU KUHAP, sentiment analysis, Instagram, Multinomial Naive Bayes, TF-IDF

I. Introduction

The rapid development of information and communication technology has significantly transformed the way people participate in the public sphere. Social media platforms, including Instagram, have become primary channels for expressing opinions, criticism, and support toward various government policies. With Indonesia's large internet user base and high level of digital engagement, social media conversations have emerged as a crucial data source for understanding public sentiment and identifying issues of concern within national discourse.

One policy that has attracted substantial public attention is the ratification of the Draft Criminal Procedure Code (RUU KUHAP). As a regulatory instrument governing criminal law procedure, the revision of the Criminal Procedure Code (KUHAP) is considered to have a broad impact on the judicial system, the protection of citizens' rights, and the transparency of law enforcement. This development has triggered diverse reactions on social media, ranging from support for legal reform to criticism of potentially problematic provisions, as well as concerns regarding their implications for future legal practices. Such diversity of perspectives highlights the need for a more in-depth analysis to understand public perceptions of the bill's ratification.

In line with the increasing volume of digital discourse, researchers have leveraged Natural Language Processing (NLP) techniques as tools to evaluate public responses to government policies [1]. Sentiment

analysis enables the identification of emotional tendencies within textual data, thereby facilitating a more systematic assessment of public opinion. Furthermore, machine learning algorithms such as Multinomial Naive Bayes, combined with Term Frequency–Inverse Document Frequency (TF-IDF) feature representation, have demonstrated effectiveness in processing short texts commonly found in social media comments [2], [3], [4].

At the same time, the development of transformer-based language models has expanded the capability to capture deeper linguistic contexts [5], [6], [7]. Nevertheless, research on public perceptions of legal policies in Indonesia continues to rely heavily on traditional machine learning approaches due to the relatively short, informal, and highly variable nature of social media data. In addition, existing studies on the Draft Criminal Procedure Code (RUU KUHAP) in digital environments predominantly emphasize normative legal analysis and traditional discourse, resulting in limited empirical mapping of public responses derived from social media data.

From a broader perspective, studies on social media sentiment analysis underscore the importance of digital data in shaping public perceptions and supporting policy evaluation processes [8], [9]. Public sentiment analysis offers insights into how society understands, accepts, or rejects public policies, while also revealing issues that are considered most salient by the public [10], [11].

However, sentiment analysis focusing on the ratification of the Criminal Procedure Code Bill, particularly using Instagram comment data, remains limited. Most existing studies tend to examine general sentiment polarity without conducting empirical analyses based on large-scale public comment data. This research gap reinforces the urgency of studies that explore public perceptions using structured computational approaches.

Therefore, this study aims to identify and analyze public sentiment toward the ratification of the Criminal Procedure Code Bill based on Instagram user comments using a TF-IDF-based sentiment analysis approach and the Multinomial Naive Bayes algorithm. By applying NLP methods that have proven effective for short and informal texts, this research is expected to provide a comprehensive depiction of public perception and contribute to the evaluation of public communication policies and practices in Indonesia.

II. Related Work

Studies on public discourse and online opinion analysis increasingly employ Natural Language Processing (NLP) techniques to understand how the public responds to government policies. Research by [1] demonstrates that text mining methods can reveal patterns of public sentiment toward policy issues using social media data, where user-generated content serves as an important indicator of social acceptance and public responses to government decisions. This approach has become particularly relevant due to the growing use of social media as a platform for discussion and criticism of legal regulations and state policies.

Advancements in NLP have also been driven by the development of transformer-based language models. Foundational studies by J and Wulandari et al. [5], [12] explain the application of Naive Bayes and TF-IDF techniques for sentiment analysis related to policy and social issues, including elections, public policy, and user opinions. Several studies [3], [4], [12] further demonstrate the effectiveness of Naive Bayes in processing local language texts and datasets. In the context of sentiment analysis, research by [13], [14] shows that transformer-based models generally achieve superior performance compared to traditional methods, particularly when handling short and informal texts commonly found on social media.

Despite the advancement of deep learning models, traditional machine learning-based approaches such as Naive Bayes remain widely used in sentiment analysis research, especially for short texts such as Instagram comments. Studies by [15], [16] confirm that Multinomial Naive Bayes (MNB) continues to serve as a robust and computationally efficient baseline for sentiment analysis in the Indonesian language, particularly when combined with Term Frequency–Inverse Document Frequency (TF-IDF) feature representation. The TF-IDF approach has been shown to effectively capture important lexical features in short texts without requiring intensive computational resources [2], [17].

Nevertheless, traditional approaches such as MNB exhibit notable limitations when applied to imbalanced datasets. Several studies, including [9], [18], report that MNB tends to underperform in classifying minority classes when data distributions are highly skewed. This issue is particularly relevant in social media research, where positive sentiment is often significantly less prevalent than neutral or negative sentiment. Such imbalance poses a considerable challenge in the analysis of controversial public policies, as supportive responses rarely appear organically in online discussions.

In addition, prior research highlights the inherent characteristics of social media data, namely short length, informal language, and high variability, which complicate the ability of traditional models to capture deeper semantic context [8]. Studies by [19], [20] indicate that online discourse related to

government policies frequently contains criticism, sarcasm, and complex opinion expressions, increasing the likelihood of misclassification by conventional sentiment analysis methods.

Although numerous studies have examined sentiment analysis in the Indonesian context, the application of sentiment analysis methods to investigate public perceptions of the ratification of the Criminal Procedure Code Bill remains limited. Existing research on the Draft Criminal Procedure Code (RUU KUHAP) predominantly emphasizes normative legal analysis or mass media discourse, rather than empirical analysis based on social media user comments. Consequently, a significant research gap persists in understanding public responses to legal regulatory changes through digital interactions.

Therefore, this study seeks to address this gap by applying TF-IDF and Multinomial Naive Bayes-based sentiment analysis techniques to Instagram comments related to the ratification of the Criminal Procedure Code Bill. This approach is expected to provide a comprehensive understanding of public perception within national legal discourse and contribute to the growing body of literature on digital opinion analysis in Indonesia.

III. Material and Methods

A. Types and Approaches of Research

This study adopts a quantitative research approach based on sentiment analysis, supported by text mining techniques within the framework of Natural Language Processing (NLP). The primary objective of this research is to analyze public perceptions of the ratification of the Draft Criminal Procedure Code (RUU KUHAP) based on user comments posted on the Instagram platform.

A quantitative approach is considered appropriate because the dataset consists of a large volume of short textual comments, which require statistical techniques and machine learning algorithms to identify objective patterns in public opinion. The NLP approach is employed to extract textual features and classify sentiments into three categories: positive, neutral, and negative. The Multinomial Naive Bayes algorithm was selected as the primary classification model due to its proven effectiveness in handling short and informal texts with diverse linguistic variations, characteristics commonly found in social media comments.

B. Data Sources and Collection

The research data were collected directly from Instagram using the Web Export feature. The data collection process involved copying the URL of Instagram posts discussing the ratification of the Criminal Procedure Code Bill and exporting all associated user comments from those posts.

The dataset consists of Instagram user comment texts related to the ratification of the Criminal Procedure Code Bill. In addition to the comment content, metadata such as the posting time and conversation structure (e.g., main comments or replies) were also recorded. Usernames were collected during the extraction process but were excluded from the analysis to protect user privacy.

Before further analysis, all comment data underwent a comprehensive cleaning process to ensure corpus quality. This process included removing duplicate comments, filtering irrelevant content such as advertisements or promotional messages, and eliminating noisy elements including URLs, hashtags, emojis, excessive punctuation, and non-alphabetic characters that do not contribute to sentiment interpretation. Subsequent preprocessing steps included lowercasing, text cleaning using regular expressions, tokenization, Indonesian stopword removal, normalization of non-standard words, and the application of light stemming when necessary. These preprocessing stages resulted in a clean and structured text corpus, which was then transformed into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) technique as a preparatory step for sentiment classification.

C. Data Analyst Model

The sentiment analysis process in this study follows a pipeline based on TF-IDF feature extraction and Multinomial Naive Bayes (MNB) classification, consisting of the following stages:

1) Feature Extraction with TF-IDF

   The Term Frequency–Inverse Document Frequency (TF-IDF) method was used to represent textual comments as numerical feature vectors. TF-IDF emphasizes terms that frequently appear within a specific document but occur less frequently across the entire corpus, thereby increasing the relevance of features associated with sentiment expression.

2) Sentiment Classification Using Multinominal Naïve Bayes

The Multinomial Naive Bayes (MNB) algorithm was employed due to its suitability for text-based sentiment analysis on social media data. This algorithm is effective in processing short texts, such as Instagram comments, which typically consist of concise and informal sentences. MNB is also sensitive to word frequency representations, making it highly compatible with TF-IDF-based feature extraction.

From a computational perspective, MNB is efficient and lightweight, enabling rapid model training and prediction even with limited computational resources. Previous studies have demonstrated that MNB performs optimally on small to medium-sized datasets, further supporting its suitability for this research.

In this study, the MNB model was trained to classify comments into three sentiment categories: positive, neutral, and negative, representing variations in public attitudes toward the ratification of the Criminal Procedure Code Bill.

3) Sentiment Analysis Workflow

The overall sentiment analysis workflow is illustrated in Figure 1 and consists of the following stages:

1. Text preprocessing,
2. Transformation of text into TF-IDF vectors,
3. Multinomial Naive Bayes model training,
4. Sentiment prediction on test data, and
5. Model performance evaluation.

This workflow was designed to ensure a systematic and structured sentiment analysis process suitable for handling short, informal, and semantically diverse social media texts.

D. Model Evaluation and Validation

Model performance was evaluated using standard metrics commonly applied in sentiment classification, including accuracy, precision, recall, and F1-score for each sentiment class. A confusion matrix was also employed to examine prediction error patterns and misclassification tendencies. In addition to quantitative evaluation, manual validation was conducted by reviewing a sample of predicted comments to ensure consistency between the model's predictions and the actual contextual meaning of public opinions expressed in the comments.

E. Research Workflow

The research workflow was conducted sequentially as follows:

1. Instagram comment extraction using Web Export based on post URLs,
2. Data preprocessing, including text cleaning, noise removal, tokenization, and normalization,
3. Transformation of textual data into TF-IDF vectors,
4. Multinomial Naive Bayes model training using training data,
5. Sentiment prediction on test data,
6. Model evaluation using accuracy, precision, recall, F1-score, and confusion matrix,
7. Interpretation of results through sentiment distribution analysis and public response patterns, and
8. Manual validation to maintain contextual consistency and prediction accuracy.

Figure 1 below illustrates the overall research workflow employed in this study. The process begins with the extraction of Instagram comments related to the ratification of the Criminal Procedure Code Bill using a web export mechanism based on post URLs. The collected data then undergoes a series of text preprocessing stages, including duplicate removal, text cleaning, lowercasing, tokenization, stopword removal, and word normalization to reduce linguistic noise and improve data quality.

Following preprocessing, the cleaned text data is transformed into numerical features using the Term Frequency–Inverse Document Frequency (TF-IDF) method, which represents the importance of words across the document corpus. These feature vectors are subsequently used to train a Multinomial Naive Bayes classifier to predict sentiment categories, namely positive, neutral, and negative. The trained model is evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and

confusion matrix analysis. Finally, the results are interpreted through sentiment distribution analysis and word cloud visualization to provide insights into public perception of the policy discussed.

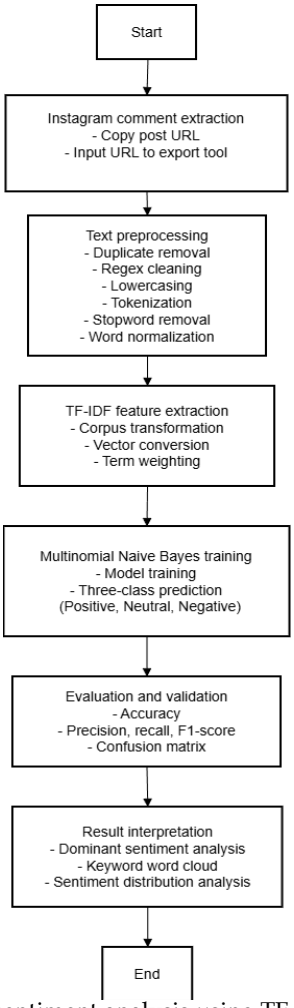

Figure 1. Research workflow for sentiment analysis using TF-IDF and Multinomial Naive Bayes.

F. Expected results

This study is expected to produce a sentiment mapping that reflects public perceptions of the ratification of the Criminal Procedure Code Bill on Instagram. Using the TF-IDF and Multinomial Naive Bayes pipeline, the classification results are expected to clearly illustrate the proportion of positive, neutral, and negative sentiments. Furthermore, this research aims to provide empirical insights into public responses to national legal policies and contribute to the development of sentiment analysis methodologies for public policy issues in Indonesia.

IV. Results and Discussion

A. Data Description and Analysis Process

This study utilizes a dataset of Instagram user comments collected from posts related to the ratification of the Criminal Procedure Code Bill. After the data extraction process, the collected comments underwent a comprehensive text preprocessing stage to ensure data quality and consistency. This process included the removal of special characters, URLs, emojis, hashtags, excessive punctuation, and irrelevant symbols. Further preprocessing steps consisted of case folding, tokenization, word normalization, and Indonesian stopword removal to eliminate non-informative words.

After preprocessing, the dataset was manually labeled into three sentiment categories: negative, neutral, and positive. The distribution of sentiment classes indicates a significant class imbalance. Negative

sentiment constitutes the largest portion of the dataset, followed by neutral sentiment, while positive sentiment appears in a considerably smaller number. Specifically, the dataset consists of approximately 285 negative comments, 232 neutral comments, and only 36 positive comments.

This imbalanced distribution reflects the dominant public reaction toward the analyzed political issue, which tends to be critical or neutral rather than supportive. From a modeling perspective, such class imbalance presents challenges for classification algorithms, particularly in identifying minority sentiment classes. Therefore, this data characteristic is an important factor influencing the performance of the sentiment classification model and is considered throughout the analysis and discussion.

Following data labeling, the dataset was divided into training and testing subsets. The preprocessed text data were then transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) method before being processed by the Multinomial Naive Bayes classification model.

B. Model Evaluation Using Classification Report and Accuracy

The performance of the sentiment classification model was evaluated using accuracy, precision, recall, and F1-score metrics, as summarized in the classification report shown in Table 1. Overall, the Multinomial Naive Bayes model achieved an accuracy of approximately 66%, indicating a moderate level of performance in classifying sentiment from Instagram comments.

A more detailed analysis reveals performance variations across sentiment classes. The negative sentiment class achieved the highest recall value, indicating that the model was able to correctly identify most negative comments. This result suggests that negative sentiment patterns were relatively dominant and well-represented in the dataset, allowing the model to learn more distinctive features for this class.

Table 1. Classification Report.

	Precision	**Recall**	**F1-score**	**Support**
Negative	0.66	0.84	0.74	58
Neutral	0.68	0.54	0.60	46
Positive	0.00	0.00	0.00	7
Accuracy			0.67	111
Macro avg	0.45	0.46	0.45	111
Weighted avg	0.63	0.67	0.64	111

The neutral sentiment class demonstrated balanced precision and recall values, indicating that the model was reasonably effective in distinguishing neutral expressions from other sentiment categories. This suggests that neutral comments, although less emotionally explicit than negative ones, still contain identifiable lexical patterns that can be captured by the TF-IDF and Multinomial Naive Bayes pipeline.

In contrast, the positive sentiment class showed precision, recall, and F1-score values of zero. This result indicates that the model failed to correctly classify any positive instances. This limitation is primarily attributed to the severely imbalanced class distribution, where positive comments represent only a small fraction of the dataset. As a result, the model was unable to learn sufficient representative patterns for the positive class, leading to the emergence of an UndefinedMetricWarning during evaluation.

Despite these limitations, the overall results indicate that the model is capable of capturing dominant sentiment trends within the dataset, particularly negative and neutral sentiments, which are the primary focus of public discourse on controversial political issues. The obtained accuracy, while moderate, is consistent with the challenges commonly encountered in sentiment analysis of short, informal social media texts with imbalanced class distributions.

C. Confusion Matrix Analysis

The confusion matrix presented in Figure 2 provides a detailed overview of the prediction performance of the Multinomial Naive Bayes model across the three sentiment classes. This visualization enables a clearer understanding of classification errors and misprediction patterns within the dataset.

For the negative sentiment class, the model correctly classified a substantial number of instances, indicating a strong capability in recognizing negative expressions. However, several negative comments were misclassified as neutral, suggesting that certain negative expressions share lexical similarities with neutral statements, particularly when criticism is expressed implicitly rather than explicitly.

In the neutral sentiment class, a moderate number of instances were correctly predicted, while a noticeable portion was incorrectly classified as negative. This misclassification indicates an overlap in

linguistic features between neutral and negative comments, which is common in political discourse where neutral statements may contain subtle evaluative language.

The most significant limitation is observed in the positive sentiment class. All positive instances were misclassified as either negative or neutral, with no correct predictions for this category. This result clearly reflects the impact of severe class imbalance, where the limited number of positive samples prevents the model from learning distinctive patterns associated with positive sentiment.

Overall, the confusion matrix highlights that the classification errors are not random but are strongly influenced by data distribution and sentiment dominance. These findings emphasize the importance of data balancing strategies or alternative modeling approaches to improve minority class recognition in future studies.

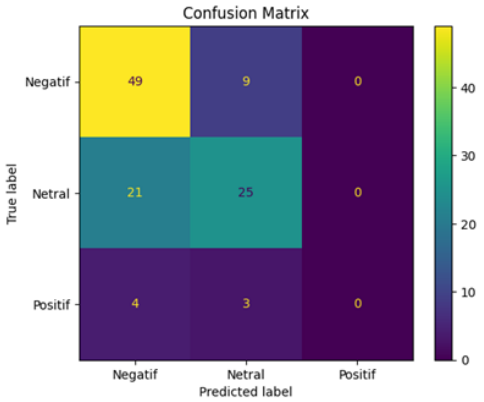

Figure 2. Confusion matrix of sentiment classification

D. Sentiment Distribution and Wordcloud

Figure 3 presents the distribution of sentiment classes obtained from the sentiment classification results. The visualization indicates that negative sentiment dominates the dataset, followed by neutral sentiment, while positive sentiment appears in a significantly smaller proportion. This imbalance reflects the tendency of public discourse on controversial legal policies to be dominated by critical and skeptical responses rather than supportive opinions. The limited presence of positive sentiment also confirms the imbalanced nature of the dataset, which affects the classification performance, particularly in detecting minority classes.

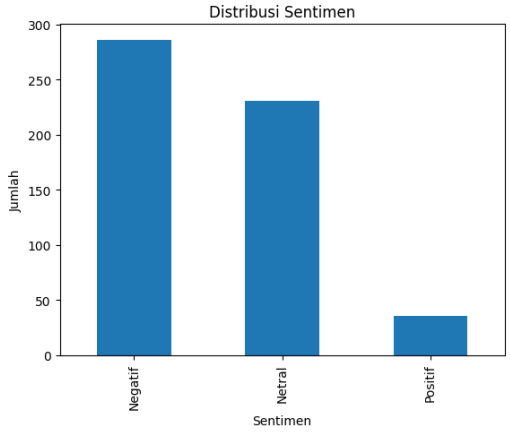

Figure 3. Distribution of sentiment classes.

The dominance of negative sentiment suggests that a large portion of Instagram users express dissatisfaction, concern, or rejection toward the ratification of the Draft Criminal Procedure Code (RUU KUHAP). Neutral sentiment, which constitutes the second-largest class, represents comments that are informational, ambiguous, or lack explicit emotional polarity. Meanwhile, the relatively small number of positive comments indicates that expressions of approval or support for the policy are less prevalent in spontaneous public discussions on social media.

To further explore the characteristics of public discourse, a word cloud visualization was generated after applying enhanced text preprocessing and stopword removal, as shown in Figure 4. The visualization highlights sentiment-relevant and issue-specific terms that frequently appear in Instagram comments.

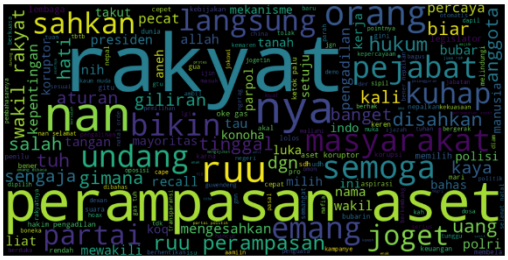

Figure 4. Word cloud visualization after stopword removal.

Dominant words such as "perampasan," "aset," "hukum," "ruu," and "korupsi" indicate that public attention is strongly focused on legal authority, asset confiscation mechanisms, and concerns regarding justice and law enforcement. The absence of common conjunctions and non-informative conversational words confirms the effectiveness of the preprocessing stage in filtering linguistic noise.

The combination of sentiment distribution analysis and word cloud visualization provides complementary insights into public perception. While Figure 3 quantitatively illustrates the imbalance and polarity of public sentiment, Figure 4 qualitatively reveals the key issues and concerns underlying those sentiments. Together, these findings demonstrate that public responses to the ratification of the RUU KUHAP are largely critical and issue-driven, emphasizing transparency, legal fairness, and the role of state authority. This result reinforces the importance of sentiment analysis as a tool for capturing public opinion and understanding societal reactions to national legal policies in the digital sphere.

E. Discussion

The findings of this study provide a comprehensive overview of public sentiment expressed through Instagram comments regarding the ratification of the Criminal Procedure Code Bill. The analysis reveals that public discourse is predominantly characterized by negative and neutral sentiments, indicating widespread criticism, skepticism, and cautious evaluation of the policy rather than overt support. This pattern reflects the nature of political discussions on social media, where controversial issues often elicit critical and emotionally charged responses.

From a methodological perspective, the Multinomial Naive Bayes model demonstrated a moderate overall accuracy of approximately 66%. While this performance may appear limited, it must be interpreted in the context of the dataset's characteristics, particularly the severe imbalance in sentiment class distribution. The dominance of negative and neutral comments enabled the model to learn representative patterns for these classes, whereas the scarcity of positive samples significantly constrained the model's ability to identify positive sentiment.

The confusion matrix and classification report further illustrate that misclassification predominantly occurs between negative and neutral classes, highlighting overlapping linguistic features commonly found in political discourse. These findings emphasize that classification errors are not merely algorithmic shortcomings but are strongly influenced by data distribution and contextual ambiguity within social media texts.

Despite these limitations, the results demonstrate that the TF-IDF and Multinomial Naive Bayes pipeline remains effective as a baseline approach for capturing dominant sentiment trends in short and informal texts. The integration of quantitative evaluation metrics with qualitative visualization, such as the word cloud, strengthens the interpretability of public opinion patterns and provides a more holistic understanding of sentiment dynamics.

This study contributes empirically to the growing body of research on sentiment analysis of public policy discourse in Indonesia by utilizing real-world social media data. Future research is encouraged to incorporate data balancing techniques, larger datasets, and alternative classification models, such as Support Vector Machines or deep learning-based approaches, to improve minority class recognition and overall model performance.

V. Conclusion

The research results show that public conversations in Instagram comment sections regarding the analyzed political issues tend to be dominated by negative sentiment. This dominance is reflected in the

data distribution, which shows a significantly greater number of negative comments than neutral or positive comments, and is further reinforced by visualization. *wordcloud* featuring vocabulary that conveys criticism, dissatisfaction, and public distrust of the issues discussed. This pattern indicates that online discussion spaces on political topics are often influenced by critical perceptions and strong emotional responses.

From a methodological perspective, the Naive Bayes model was able to classify negative and neutral sentiment with a moderate accuracy of 66% but failed to identify positive sentiment due to unequal data distribution. The lack of predictions in the positive class and the emergence of *Undefined Metric Warning* confirmed that data imbalance has a significant impact on model performance. This finding place the importance of data balancing strategies, such as *oversampling* or exploration of alternative classification methods, to improve the reliability of the analysis in subsequent studies.

Overall, this study demonstrates that social media-based sentiment analysis can provide a clear picture of the direction of public opinion, while also highlighting methodological challenges that need to be addressed so that the model can capture variations in sentiment more accurately and representatively.

Conflicts of Interest

The author declares no conflict of interest.

Author Contributions Statement

Dede Yayan Suciyana was responsible for the conceptualization of the study, data collection, preprocessing, model implementation, and manuscript drafting. Fathoni Mahardika and Dani Indra Junaedi contributed to research supervision, methodological validation, critical review of the manuscript, and provided substantive feedback to improve the clarity and scientific rigor of the study. All authors have read and approved the final version of the manuscript.

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