Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th February 2026. Vol. 5. No. 2; e-ISSN: 2808-4519

Sentiment Analysis of Public Opinion on the Pertalite Fuel Issue in YouTube Comments Using the Naïve Bayes Method

Ernika Frevita Ayu Septiani[1]*, Fandi Ahmad Ramadhani[2], Harun Al Rosyid[3]

[1,2,3]Universitas Negeri Surabaya
ernika.22058@mhs.unesa.ac.id[1]*, fandi.22073@mhs.unesa.ac.id[2], harunrosyid@unesa.ac.id[3]

Abstract

The issue of Pertalite fuel (BBM Pertalite) has generated widespread public reactions on social media, particularly on the YouTube platform, where users actively express opinions through comment sections. This study aims to analyze public sentiment toward the Pertalite fuel issue based on YouTube comments using a text mining approach and the Naïve Bayes classification algorithm. The dataset consists of approximately 3,000 YouTube comments collected via the YouTube Data API and processed through several text preprocessing stages, including cleaning, normalization, tokenization, stopword removal, and stemming. Sentiment labeling was performed using a lexicon-based approach, followed by feature extraction using Term Frequency–Inverse Document Frequency (TF-IDF). The data were divided into training and testing sets with an 80:20 ratio. Experimental results indicate that the Naïve Bayes model achieved an accuracy of 69.67%, with negative sentiment dominating public discourse both in terms of comment frequency and user engagement measured by likes. These findings suggest a prevailing public dissatisfaction with the Pertalite fuel issue and highlight the usefulness of social media–based sentiment analysis as a data-driven instrument for understanding public perception. The results of this study provide valuable insights that can support the evaluation of energy policies and demonstrate the potential of sentiment analysis in policy-related public opinion studies.

Keywords: *Sentiment Analysis, Pertalite Fuel, Youtube, Naïve Bayes, Text Mining*

1. Introduction

Fuel oil (BBM) is a strategic commodity that plays a vital role in supporting economic activities and public mobility in Indonesia. Pertalite, as a subsidized fuel, is intended to meet the energy needs of lower- to middle-income communities. Consequently, issues related to its price, distribution, or usage restrictions frequently generate widespread public responses. Fuel-related issues affect not only economic aspects but also social justice, national stability, and public trust in government. Therefore, understanding public sentiment and responses is an essential element in evaluating national energy policies[1], [2].

The development of social media has transformed patterns of public communication in expressing opinions on government policies. YouTube has emerged as one of the most actively used platforms for consuming information while simultaneously expressing opinions through comment sections. The open and spontaneous nature of YouTube comments, combined with their large volume, enables the formation of a more natural representation of public opinion compared to conventional surveys. Numerous studies indicate that social media serves as an effective data source for analyzing public sentiment and opinion on social, political, and public policy issues [3], [4], [5]. YouTube comments, in particular, provide a spontaneous and open representation of public opinion [6], reflecting public responses and perceptions of policy issues rapidly through online, data-driven approaches [7].

However, the large volume of comments renders manual opinion analysis inefficient and potentially biased. To address this challenge, text mining and data mining approaches are widely employed to process textual data automatically. Sentiment analysis is one of the primary techniques in text mining, aimed at identifying the polarity of public opinion toward a particular issue—whether positive, negative, or neutral [8], [9]. This approach has been extensively applied in studies of public policy, economics, and energy to understand public perceptions in a data-driven manner [10], [11].

In sentiment analysis, the selection of classification algorithms significantly influences the accuracy of results. The Naïve Bayes method is one of the most commonly used classification algorithms due to its simple probabilistic model, computational efficiency, and ability to handle high-dimensional text data [11], [12]. Various studies have demonstrated that Naïve Bayes exhibits stable and competitive performance in social media sentiment analysis, including for Indonesian-language data that are unstructured and contain informal language variations [13], [14]. The method remains effective for large-scale datasets with imbalanced class distributions [13].

Previous studies have demonstrated the effectiveness of sentiment analysis in examining public opinion on government policies. Nugroho et al. [2] and Wahyudi et al. [13] showed that sentiment analysis can provide an objective overview of public responses to public policies. Kurniawan et al. [15] and Pratama and Adiwijaya [14] confirmed that the Naïve Bayes method is effective for classifying public opinion sentiment on Indonesian-language social media. At the global level, Medhat et al. [1], Liu [8], and Giachanou and Crestani [10] emphasized that sentiment analysis is a relevant approach for understanding public opinion at scale. Nevertheless, studies that specifically utilize YouTube comments to analyze Indonesian public sentiment toward the Pertalite fuel issue remain relatively limited.

Based on this research gap, this study aims to analyze public sentiment toward the Pertalite fuel issue through YouTube comments using the Naïve Bayes method. The specific objectives are to identify trends in public sentiment and to evaluate the performance of the Naïve Bayes method in the context of energy policy sentiment analysis. The results are expected to contribute academically to the development of artificial intelligence and social media-based sentiment analysis research while also providing data-driven insights that can serve as input for public policy evaluation in the energy sector.

2. Research Methods

This study adopts a quantitative research approach using text mining techniques to analyze public sentiment toward the Pertalite fuel issue based on YouTube comments. The overall research workflow consists of several sequential stages, including problem identification, data collection, data preprocessing, sentiment labeling, feature extraction, sentiment classification using the Naïve Bayes algorithm, and performance evaluation. The complete workflow of the proposed method is illustrated in Fig. 1.

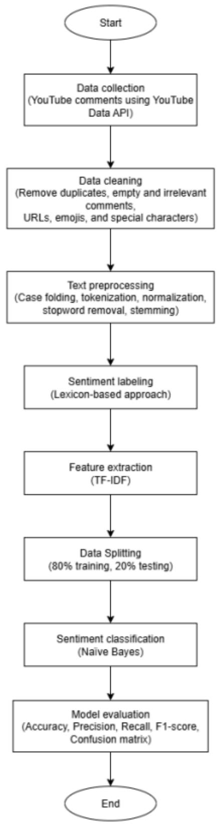

Fig. 1: Flowchart of the sentiment analysis process using the Naïve Bayes method

2.1. Problem Identification

The initial stage of the research involved identifying issues related to the high public response to the Pertalite fuel issue on social media, particularly YouTube. The main research questions addressed were: (1) What is the tendency of public sentiment toward the Pertalite fuel issue? and (2) To what extent is the Naïve Bayes method able to effectively classify user comment sentiment?

2.2. Data collection

The data used in this study consist of YouTube user comments related to the Pertalite fuel issue. Data collection was conducted on YouTube videos discussing policies, discourse, or news related to Pertalite fuel. Comments were collected using the YouTube Data API with specific criteria, including video upload timespan and keyword relevance. The entire data collection and processing process was carried out using Google Colaboratory (Google Colab) as a cloud-based computing environment with the Python programming language. The collected dataset comprised approximately 3,000 comments, which were then stored in text format for further processing and analysis.

2.3. Data preprocessing

Data preprocessing was performed to clean and normalize the raw text data to ensure suitability for sentiment analysis. The preprocessing steps include:

1. Cleaning and tokenization, which remove punctuation, numbers, URLs, emojis, and special characters, and split the text into individual word tokens.
2. Case folding, which converts all text into lowercase to maintain consistency.
3. Tokenization, which splits the cleaned text into individual word tokens based on whitespace separation.
4. Normalization, which converts informal, abbreviated, or non-standard words into their standardized forms to ensure textual consistency.
5. Stopword removal, which eliminates commonly used words that do not carry sentiment information.
6. Stemming, which transforms words into their root forms according to Indonesian linguistic rules.

The output of this stage is a structured and normalized textual dataset that is ready for feature extraction.

2.4. Data Labeling

Data labeling was performed automatically using a lexicon-based sentiment labeling approach. At this stage, each comment was analyzed against an Indonesian sentiment lexicon containing a list of positive and negative words along with their associated weights. The labeling process was conducted by calculating a sentiment score for each comment based on the accumulated weights of the words present. Comments were classified into three sentiment categories:

1. Positive sentiment: if the sentiment score is positive.
2. Negative sentiment: if the sentiment score is negative.
3. Neutral sentiment: if the sentiment score is zero or within a predetermined threshold.

The lexicon-based approach was chosen because it provides objective and consistent initial labeling without relying on manual annotation, making it suitable for large volumes of comment data. These labeling results were subsequently used as labeled data in the training and testing process of the Naïve Bayes model.

2.5. Feature Extraction

Feature extraction was performed to transform text data into numerical representations. The method employed was Term Frequency-Inverse Document Frequency (TF-IDF). This representation aims to capture the weight of word occurrences in each comment, enabling processing by the Naïve Bayes algorithm.

2.6. Classification Using the Naive Bayes Method

At this stage, the feature-extracted data were classified using the Naïve Bayes method. This algorithm operates by calculating the probability of a word appearing in each sentiment class and determining the class with the highest probability as the classification result. The classification process was conducted by dividing the dataset into training and testing sets using an 80:20 split ratio.

2.7. Model Evaluation

Model evaluation was conducted to measure the performance of the Naïve Bayes method in classifying sentiment. Evaluation metrics used included accuracy, precision, recall, and F1-score. Additionally, a confusion matrix was employed to observe the distribution of classification results within each sentiment class.

2.8. Result Analysis

The final stage of the research involved analyzing the sentiment classification results. The analysis was used to determine the tendency of public sentiment toward the Pertalite fuel issue based on YouTube comments. Furthermore, this analysis evaluates the effectiveness of the Naïve Bayes method in the context of public policy sentiment analysis.

3. Results And Discussion

3.1. YouTube Comment Sentiment Classification Results

This study aims to analyze public sentiment regarding the Pertalite fuel issue on YouTube using the Naïve Bayes algorithm. The analyzed data consist of user comments that have undergone preprocessing and lexicon-based sentiment labeling.

Model testing, conducted with an 80:20 split between training and testing data, demonstrated that the Naïve Bayes algorithm achieved an accuracy of 69.67%. This value indicates that the model is capable of classifying comment sentiment with a reasonably good level of accuracy, particularly considering the unstructured nature of YouTube comment data, which contains informal language and exhibits imbalance in the amount of data across sentiment classes.

Detailed model performance evaluation results are presented in Table 1, which displays the precision, recall, and F1-score values for each sentiment class.

Table 1: Naïve Bayes Model Evaluation

Accuracy: 0.6967509025270758				
	precision	**recall**	**f1-score**	**support**
Negative	0.68	0.99	0.80	345
Positife	0.92	0.22	0.35	206
Neutral	0.00	0.00	0.00	3
accuracy			0.70	554
macro avg	0.53	0.40	0.39	554
weighted avg	0.76	0.70	0.63	554

3.2. Evaluation Based On Confusion Matrix

Based on the confusion matrix, the majority of comments with negative sentiment were correctly classified by the model. This is demonstrated by the high recall value (0.99) in the negative class, indicating that almost all comments containing complaints and criticisms regarding the Pertalite issue were correctly identified.

However, a number of neutral comments were misclassified as negative sentiment. This suggests that neutral comments containing language related to policy, pricing, or fuel often contain an implicit context of dissatisfaction, causing them to be classified into the negative class by the model.

Meanwhile, the model's performance in recognizing positive sentiment remained low, as evidenced by a recall value of only 0.22. This is attributed to the very small amount of positive sentiment data in the dataset, meaning the model lacks sufficient data representation to optimally learn the characteristics of positive sentiments. This class imbalance phenomenon is common in social media sentiment analysis research, particularly on public policy issues that tend to generate critical responses.

3.3. Public Comment Sentiment Distribution

The distribution of comments based on sentiment is presented in Table 2. The results demonstrate that negative sentiment dominates public conversations regarding the Pertalite issue, followed by neutral sentiment, while positive sentiment accounts for a very small portion.

Table 2: Distribusi Jumlah Komentar per Sentimen

Sentiment	**Number Of Comment**
Negatife	1723
Neutral	1032
Positife	15

To clarify this distribution, a bar graph visualization is presented in Figure 1. The graph illustrates that negative sentiment has the highest number of comments compared to neutral and positive sentiment.

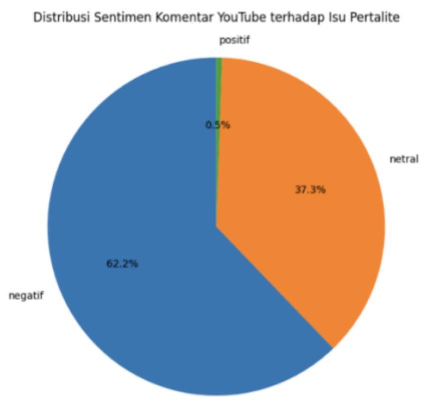

Fig. 2: Distribution of public sentiment toward the Pertalite fuel issue

The dominance of negative sentiment indicates that the majority of YouTube users responded with complaints, criticism, and dissatisfaction regarding the Pertalite fuel issue. This finding reflects public concern and discontent with energy policies related to subsidized fuel.

3.4. Like Analysis as a Supporter of Sentiment

In addition to comment frequency, this study also considered the number of likes as a supporting indicator to assess the level of user response and agreement with each sentiment. A summary of the number of comments, total likes, and average likes based on sentiment is shown in Table 3.

Table 3: Number of Comments and Likes by Sentiment

Sentiment	Number Of Comments	Total Likes	Average Likes
Negative	1723	2191	1.271619
Neutral	1032	1064	1.031008
Positive	15	3	0.200000

Based on this table, negative sentiment not only dominates in terms of comment frequency but also receives the highest total and average likes. This indicates that negative comments receive greater attention and support from other users, suggesting a strong resonance with public opinion.

Conversely, positive sentiment has a very low number of comments and minimal likes, indicating a negligible positive public response to the Pertalite issue. Therefore, the number of likes can be used as an additional indicator to strengthen sentiment analysis results, particularly in measuring the resonance of public opinion on social media platforms.

3.5. General Discussion

The results of this sentiment analysis indicate that public perception of the Pertalite fuel issue on YouTube tends to be predominantly negative. This finding is reinforced by the high level of interaction in the form of likes on negative comments, reflecting agreement and support from other users with critical opinions expressed.

The use of the Naïve Bayes algorithm in this study proved capable of providing a general overview of public sentiment trends with reasonable accuracy (69.67%). However, the model faces challenges in detecting minority sentiments, particularly positive sentiment, due to severe class imbalance in the dataset. The positive class comprises only 15 comments out of 3,000, making it difficult for the model to learn the distinctive characteristics of positive sentiment effectively.

Despite these limitations, the combination of sentiment analysis and engagement indicators (likes) provides a more comprehensive understanding of public responses on social media. The high engagement with negative comments suggests that critical opinions regarding the Pertalite fuel issue resonate strongly with the YouTube audience, indicating widespread public concern about energy policy matters.

These findings have important implications for policymakers. The predominance of negative sentiment suggests that the Pertalite fuel policy may require re-evaluation or improved communication strategies to address public concerns. Social media-based sentiment analysis can serve as an early warning system for policymakers to identify emerging public dissatisfaction and respond proactively.

Future research should address the class imbalance issue through techniques such as oversampling (SMOTE), undersampling, or the use of ensemble methods. Additionally, comparing the performance of Naïve Bayes with other algorithms such as Support Vector Machine (SVM), Random Forest, or deep learning approaches could provide insights into optimal classification methods for imbalanced sentiment data. Incorporating temporal analysis to track sentiment changes over time would also enhance the utility of sentiment analysis for policy monitoring.

4. Conclusion

This study successfully analyzed public sentiment toward the Pertalite fuel issue through YouTube comments using a text mining approach and the Naïve Bayes algorithm. The results demonstrate that negative sentiment dominates public opinion, both in terms of comment frequency and user engagement (likes), indicating high public dissatisfaction with the issue. The Naïve Bayes model achieved a classification accuracy of 69.67%, demonstrating reasonably good performance considering the characteristics of YouTube comment data, which are unstructured, contain informal language, and exhibit significant sentiment class imbalance.

These findings demonstrate that social media-based sentiment analysis can serve as a supporting instrument for understanding public responses to energy policies in a data-driven manner. The results of this study have the potential to inform public policy evaluation, particularly in responding to public perceptions of subsidized fuel policies.

Future research is recommended to employ a more balanced dataset, apply more sophisticated classification methods or ensemble techniques, and compare multiple algorithms to improve model performance and analysis depth. Additionally, incorporating temporal sentiment analysis and exploring deep learning approaches could provide richer insights into public opinion dynamics regarding energy policy issues.

Acknowledgement

The authors would like to express their gratitude to all parties who contributed to the completion of this study. Appreciation is extended to the reviewers and editors for their valuable comments and suggestions, which helped improve the quality of this manuscript. The authors also acknowledge the availability of public data sources and supporting tools that facilitated the data collection and analysis process.

References

[1] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications : A survey," *Ain Shams Eng. J.*, vol. 5, no. 4, pp. 1093–1113, 2014, doi: 10.1016/j.asej.2014.04.011.
[2] R. Nugroho, E. Hidayat, and E. Prasetyo, "Pemanfaatan media sosial untuk analisis opini publik terhadap kebijakan pemerintah," *J. Ilmu Sos. dan Hum.*, vol. 10, no. 2, pp. 256–266, 2021, doi: 10.23887/jish-undiksha.v10i2.32456.
[3] B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," *Found. Trends Inf. Retr.*, vol. 2, no. 1–2, pp. 1–135, Jan. 2008, doi: 10.1561/1500000011.
[4] A. Pak and P. Paroubek, "Twitter as a Corpus for Sentiment Analysis and Opinion Mining," pp. 1320–1326.
[5] K. Ravi and V. Ravi, "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications," *Knowledge-Based Syst.*, vol. 89, pp. 14–46, 2015, doi: https://doi.org/10.1016/j.knosys.2015.06.015.
[6] A. Alsaeedi and M. Z. Khan, "A Study on Sentiment Analysis Techniques of Twitter Data," vol. 10, no. 2, pp. 361–374, 2019.
[7] E. Cambria, "Affective Computing and Sentiment Analysis," *IEEE Intell. Syst.*, vol. 31, no. 2, pp. 102–107, 2016, doi: 10.1109/MIS.2016.31.
[8] B. Liu, "Sentiment Analysis and Opinion Mining," no. May, 2012.
[9] R. Feldman, "Techniques and Applications for Sentiment Analysis," *Commun. ACM*, vol. 56, pp. 82–89, 2013, doi: 10.1145/2436256.2436274.
[10] A. Giachanou and F. Crestani, "Like It or Not : A Survey of Twitter Sentiment Analysis Methods," vol. 49, no. 2, 2021.
[11] A. Qazi, R. G. Raj, G. Hardaker, and C. Standing, "A systematic literature review on opinion types and sentiment analysis techniques," *Internet Res.*, vol. 27, no. 3, pp. 608–630, 2017, doi: https://doi.org/10.1108/IntR-04-2016-0086.
[12] F. Informatik and T. Joachims, "K unstliche Intelligenz Text Categorization with Support Vector Machines : Learning with Many Relevant Features," 1998.
[13] R. Wahyudi, Y. A. Sari, and M. A. Fauzi, "Analisis sentimen masyarakat terhadap kebijakan pemerintah menggunakan Naïve Bayes," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 8, no. 3, pp. 567–574, 2021, doi: 10.25126/jtiik.202183394.
[14] B. A. Pratama and Adiwijaya, "Analisis sentimen pada Twitter menggunakan metode Naïve Bayes dengan seleksi fitur chi-square," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 12, pp. 6303–6310, 2018, [Online]. Available: https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/3444
[15] D. Kurniawan, N. Hidayat, and L. Fanani, "Analisis sentimen opini publik pada media sosial menggunakan metode Naïve Bayes," *J. RESTI*, vol. 4, no. 5, pp. 882–889, 2020, doi: 10.29207/resti.v4i5.2356.