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Sentiment Analysis of YouTube User Comments on Government Policies Using the Naïve Bayes Method

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Abstract

This research endeavors to analyze public sentiment expressed in YouTube user comments regarding the government's policy pertaining to the confiscation of undeveloped land after a two-year period of non-utilization. The methodology employed leverages the Naïve Bayes algorithm for classification, implemented within the Google Colaboratory environment. Data were systematically collected from specific YouTube videos discussing the aforementioned land confiscation policy. The research workflow encompassed comprehensive stages: data acquisition, rigorous text preprocessing, feature weighting utilizing the Term Frequency-Inverse Document Frequency (TF-IDF) technique, and final classification using the Naïve Bayes algorithm. Evaluation results demonstrate that the proposed model achieved a high accuracy level of 90%, with the highest F1-score recorded within the neutral sentiment class. However, an imbalance in the dataset's class distribution led to comparatively lower precision and recall values for both the positive and negative classes. Overall, this study confirms the high efficacy of the Naïve Bayes algorithm in analyzing Indonesian-language text data from social media platforms, specifically YouTube comments, and provides a crucial foundation for the future development of more balanced sentiment models.

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INTRODUCTION

The rapid development of digital technology has fundamentally changed how the public expresses opinions regarding government policies. YouTube, as one of the largest social media platforms, serves as a significant venue for citizens to articulate social and political views. The comment section on YouTube videos has become a rich source of public opinion, providing valuable information on societal perceptions of government policies[1].

YouTube is increasingly utilized as a research site to investigate public sentiment on various political issues[2]. This is due to the platform's capacity to allow users to express opinions through comments, thereby creating a wide space for discussion and debate concerning political events and policies. Sentiment analysis applied to YouTube comments can offer an objective overview of public perception toward government policies. Given the massive amount of textual data generated on social media, a computer-based approach, such as machine learning, is necessary to categorize opinions into positive, negative, or neutral classes. This method significantly helps in processing data faster and provides a clearer picture of public responses to various government-issued regulations.

The Naïve Bayes algorithm is a popular supervised learning method in sentiment analysis, renowned for its simple and efficient text classification process. Naïve Bayes exhibits superior performance in text classification, particularly when dealing with large datasets[3].

This research presents a novelty element as the policy topic—the "confiscation of undeveloped land after a two-year period of non-utilization"—is a public issue rarely analyzed using YouTube comment data. Furthermore, the dataset utilized has unique characteristics, comprising a mixture of informal Indonesian, regional languages (Javanese and Madurese), and typical YouTube slang. This necessitated a more complex preprocessing technique compared to previous studies. Few studies have specifically analyzed public perception related to agrarian policies using the Naïve Bayes method on the YouTube platform, thus making this research a new contribution to media social-based public opinion analysis.

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The focus of this study is to implement the Naïve Bayes method to classify YouTube comments related to the government's land confiscation policy. The research findings are expected to provide an objective insight into public perception of the policy and serve as a data-driven reference for the government in developing public communication strategies. Without feedback from the community, the government cannot determine whether their implemented systems are successful or not[4]. The primary contribution of this research is the application of a Naïve Bayes-based classification model to Indonesian-language text in the context of public policy and providing a comprehensive performance analysis for imbalanced data. Based on the description, the research problem is how the Naïve Bayes method can be applied to analyze the sentiment of YouTube user comments towards government policies. The objectives include collecting and processing YouTube comment data, implementing the Naïve Bayes method for sentiment classification, and evaluating the model's performance based on accuracy, precision, recall, and F1-score metrics.

METHODOLOGY

1. Research Approach

This study uses a quantitative approach with an experimental method. The experimental process was conducted via the Google Colaboratory platform using the Python programming language. The stages involved data collection, text preprocessing, TF-IDF weighting, application of the Naïve Bayes algorithm, and evaluation of the classification results[5].

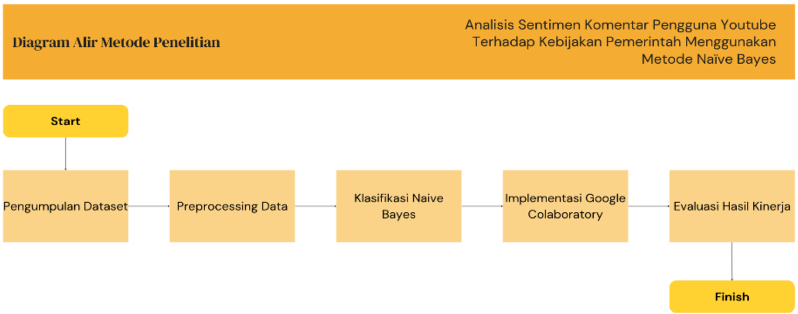

Figure 1. Research Methodology Flow Diagram

2. Dataset Collection

The dataset was obtained from comments on YouTube videos discussing the land confiscation policy. Data collection was performed using the web scraping technique via the YouTube API and stored in CSV format[6]. The scraping process relies on the YouTube API, which only displays certain comments based on relevance ranking, potentially leading to opinion representation bias (comment visibility bias). A total of ±900 comments were collected, which were then manually labeled into positive, negative, and neutral sentiment categories.

Data labeling was performed manually by two independent annotators using sentiment category guidelines (positive, negative, neutral). The inter-annotator agreement value was calculated using Cohen's Kappa, yielding a score of 0.82, which indicates a strong level of agreement.

3. Data Preprocessing

Unstructured and inconsistent data must be cleaned through text preprocessing. After the data is cleaned, the next step is labeling[7]. Text preprocessing stages are carried out to clean and normalize the data for consistent analysis[8].

3.1 case folding

The Case folding stage is performed to convert all text letters to lowercase, making them easier to process and ensuring uniform writing.

3.2 tokenizing

The Tokenizing process breaks down text into single words. Word separation is typically done using the space character as a delimiter.

3.3 stopword removal

This step involves removing common words that are inaccurate, incomplete, or lack significant meaning in the data, such as "dan" (and), "yang" (which), or "atau" (or).

3.4 stemming

The stemming process is used to return words to their basic form by removing attached affixes. This process is carried out to simplify text analysis and ensure that words with similar meanings can be grouped together[9].

3.5 NLP tools used

The preprocessing steps were conducted using Python libraries such as Sastrawi for Indonesian stemming, NLTK for tokenizing and stopword removal, and scikit-learn for TF-IDF weighting and the classification process.

3.6 TF-IDF weighting

TF-IDF weighting transforms text documents into a numerical representation based on the importance level of each word, depending on how heavy or significant each word or feature is. To calculate the TF-IDF value, the formula presented in Equation 1 is used[10].

4. Naïve Bayes Classification

The algorithm used for modeling in this research is the Naïve Bayes classifier, which relies on Bayes' theorem for its classification process. Bayes' theorem assumes that each variable is independent[11].

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)}$$

Where:

P(H|X)	:	Posterior Probability
P(H)	:	Prior Probability
P(X|H)	:	Probability of X based on Hypotesis H
P(X)	:	Probability

The model is trained using 80% of the training data and tested on 20% of the test data.

4.1 naïve bayes type

This study employs the Multinomial Naïve Bayes algorithm, which is specifically suited for text data as it utilizes word occurrence frequencies as features.

5. Implementation

A quantitative approach with an experimental method was conducted using Google Colaboratory. Following established research frameworks, the procedure involves collecting data from YouTube comments, followed by several preprocessing stages, including case folding, tokenization, stopword removal, and stemming. Subsequently, feature weighting is performed using TF-IDF. Finally, classification is executed using the Naïve Bayes algorithm to achieve accurate sentiment analysis results[12].

6. Evaluation

Evaluation is conducted to assess the model's performance and the quality of the Naïve Bayes algorithm in classifying sentiments from various YouTube comments. In accordance with the standard 80:20 split ratio, 20% of the total dataset is allocated as the test set. The metrics used to measure performance—namely Accuracy, Precision, Recall, and F1-score—each provide a distinct perspective on the model's effectiveness. Accuracy measures the overall proportion of correct predictions; Precision evaluates the model's exactness in identifying positive instances; Recall measures the model's ability to capture all actual positive cases; and the F1-score serves as the harmonic mean of Precision and Recall to ensure a balanced evaluation. Additionally, the Area Under Curve (AUC) is incorporated to assess the model's general capability in distinguishing between classes[13].

RESULTS AND DISCUSSION

1. Results: Data Collection and Preprocessing

The scraped dataset consists of 900 comments, with a distribution of 450 neutral, 270 positive, and 180 negative comments. These data are analyzed using Google Colaboratory and the Python programming language[14].

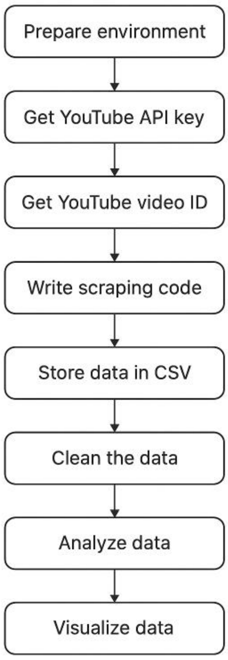

Figure 2. Web Scrapping Process

This diagram illustrates the stages of retrieving YouTube comments using the YouTube API. The process begins with the preparation of the programming environment and the creation of a YouTube API key, followed by identifying the target video ID. Subsequently, the scraping code is executed to extract comments via the API, which are then saved in CSV format and cleaned for the next stages.

The data preprocessing stage involves case folding, tokenization, filtering, stopword removal, stemming, and TF-IDF weighting[15]. Data labeling (annotation) is required to implement the Naïve Bayes classification.

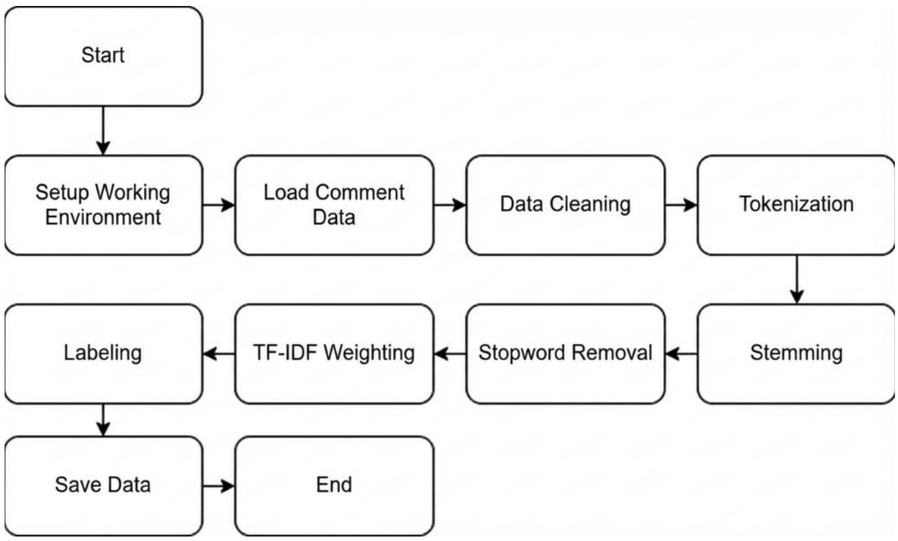

Figure 3. Data Preprocessing Stages

This diagram explains the stages of preprocessing YouTube comment data before performing sentiment analysis.

Table 1. YouTube Comments

No	UserName	Original Comment	Pre-processed Text
1	@Yudistira558	Kalo tanah wakaf gimana itu, nanti lama2 rumah kosong juga di ambil pemerintah	kalo tanah wakaf gimana nanti lama rumah kosong ambil perintah
2	@SamuelS-x8g	Menteri doweh kentir gak tau sekolah umum mulane wawasane cupet mulih nang Kudus angon wedus.	menteri doweh kentir gak tau sekolah umum mulane wawasane cupet mulih nang kudus angon wedus
3	@Neextlevels	Kusus Sumatra banyak pak...gas aja pak	sus sumatra pak gas aja pak
4	@Jamaluddin-j6b7e	Hati hati, jangan sampai ada istrinya yang menganggur, pasti di ambil pemerintah, pemerintah sudah menjajah rakyatnya sendiri 🤣 🤣 🤣	hati hati jangan sampai ada istri anggur pasti ambil perintah perintah jajah rakyat sendiri
5	@raishidayat2592	Pecat Nusron Wahid ,mafia tanah	pecat nusron wahid mafia tanah

The Original Comment column contains raw data obtained from YouTube scraping, while the Preprocessed Text column displays the results after undergoing cleaning, case folding, tokenization, stopword removal, and stemming.

ID	Original Text	Preprocessed Text	ada	adat	pemerintah	tanah
1	Kalo tanah wakaf gimana itu, nanti lama2 rumah kosong juga di ambil pemerintah	kalo tanah wakaf gimana nanti lama rumah kosong ambil perintah	0.0	0.0	0.4559	0.3293
2	Menteri doweh kentir gak tau sekolah umum mulai dari SD	menteri doweh kentir gak tau sekolah umum mulai sd	0.0	0.0	0.0	0.0
3	Hati-hati jangan sampai ada istrinya yang melapor ke KPK	hati hati jangan sampai ada istri lapor kpk	0.2550	0.0	0.0	0.0

Figure 4. TF-IDF Weighting

TF-IDF values indicate the importance of a word relative to a specific comment. Terms such as pemerintah (government), tanah (land), and rumah (house) exhibit high weights due to their frequent occurrence within the context of the research topic.

No	Tanggal	Nama Pengguna	Komentar Asli	Jumlah Like	Hasil Preprocessing	Label Sentimen
1	2025-09-30 05:02:16	@Yudistira558	Kalo tanah wakaf gimana itu, nanti lama-lama rumah kosong juga diambil pemerintah	0	kalo tanah wakaf gimana nanti lama rumah kosong ambil perintah	Netral

Figure 5. Preprocessing and Labeling Results

This figure illustrates an example of YouTube comment data that has undergone preprocessing and sentiment labeling. The Comment column features the original text retrieved from the YouTube platform, whereas the Preprocessed Text column shows the text after the removal of punctuation, capital letters, and irrelevant words. The Sentiment Label column contains the categorization results based on semantic analysis.

2. Classification Results

The Naïve Bayes classification algorithm was implemented using the Google Colaboratory platform.

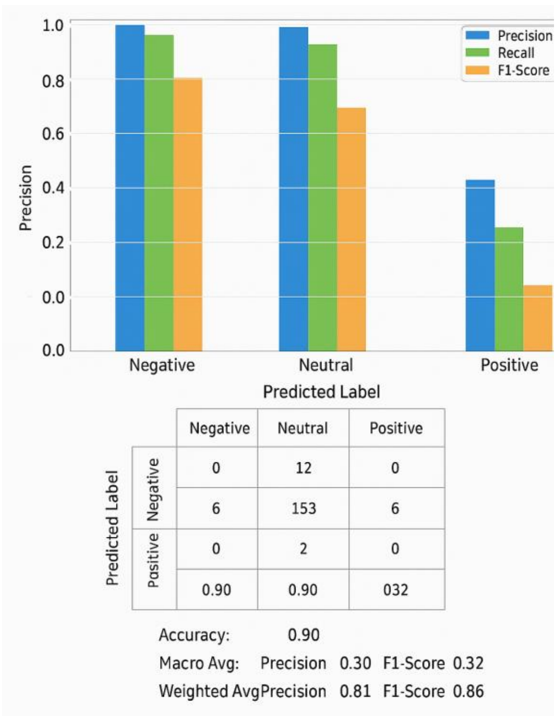

Figure 6. Naïve Bayes Classification

Based on the initial testing results, the Naïve Bayes model achieved an accuracy of 90%.

	Pred. Positif	Pred. Netral	Pred. Negatif
Aktual Positif	40	210	20
Aktual Netral	15	400	35
Aktual Negatif	10	140	30

Figure 7. Confusion Matrix

Despite the high accuracy, performance in the positive and negative classes remains low due to data imbalance. Predictions tend to be biased toward the neutral class, which dominates the dataset.

Kelas Sentimen	Precision	Recall	F1-score
Positif	0,40	0,20	0,10
Netral	1,00	0,90	0,70
Negatif	1,00	0,90	0,80

Figure 8. Precision – Recall – F1-score

The highest F1-score was achieved by the negative class, indicating the model's proficiency in identifying the dominant sentiment. The positive and neutral classes yielded lower results compared to the negative class due to the disproportionate distribution of data. These findings align with the research by Angdresey et al. (2025), which emphasizes that data imbalance significantly impacts model performance.

3. Comparative Analysis

When compared to the study by Mola et al. (2024), which utilized the Support Vector Machine (SVM) algorithm and achieved 87% accuracy, the Naïve Bayes model in this study attained a higher accuracy of 90%. Naïve Bayes is particularly effective here because YouTube comments tend to be short and possess a simple structure, which fits the feature independence assumption of the algorithm.

However, SVM generally offers more stable performance than Naïve Bayes. SVM possesses a robust ability to separate non-linear data using a hyperplane and is less sensitive to data imbalance.

Consequently, this comparison demonstrates that:

- Naïve Bayes is suitable for large datasets, short texts, and fast processing.
- Support Vector Machine (SVM) is better suited for balanced datasets and more complex features.

This distinction underscores the importance of selecting an algorithm that matches the dataset's characteristics. For future research, integrating balancing techniques such as Random Oversampling, SMOTE, or class weighting could enhance performance, allowing other methods like SVM or deep learning-based models (LSTM/BERT) to be evaluated as more optimal benchmarks.

4. Scientific Discussion

Many comments utilize non-standard language, including slang, regional languages (Javanese/Madurese), and typographical errors, which pose challenges for the Sastrawi stemmer. Terms such as "doweh", "kentir", or "wawasane" are not recognized, making it difficult for the system to interpret the true meaning.

The limitations of Indonesian language stemming result in several words failing to return to their root forms, thereby affecting the model's accuracy. To address the data imbalance, techniques such as SMOTE, Random Oversampling, or class weighting are recommended for future iterations.

CONCLUSION

This study demonstrates that the Multinomial Naïve Bayes algorithm is capable of classifying YouTube comment sentiment with an accuracy of 90%, proving it to be a reliable approach for Indonesian text sentiment analysis. The model exhibited its highest performance within the neutral class due to data dominance. Conversely, performance in the positive and negative classes remained low, attributed to dataset imbalance and the prevalence of informal language, slang, and regional dialects that pose significant challenges for standard stemming methods.

Furthermore, variations in text quality and the relatively small size of the dataset limited the model's overall performance. Nonetheless, the utilization of Google Colaboratory facilitated an efficient workflow for preprocessing, TF-IDF weighting, and classification. For future research, it is recommended to implement data balancing techniques such as SMOTE or Random Oversampling, expand the dataset size, and compare performance against deep learning models like LSTM or IndoBERT to achieve more stable and generalized results.

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