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Sentiment Analysis of Public Opinion on RUU KUHAP 2025 Using Multinomial Naïve Bayes and Random Oversampling

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Abstract

The ratification of the Draft Criminal Procedure Code (RUU KUHAP) in 2025 has triggered a significant wave of public reaction on social media, particularly on YouTube. Understanding these public sentiments is crucial for evaluating the legislative performance of the House of Representatives (DPR). This study aims to classify public opinion into positive and negative sentiments using the Multinomial Naïve Bayes algorithm. The dataset consists of 2,370 user comments collected from YouTube. To address the challenge of unstructured text, a comprehensive pre-processing pipeline was implemented, including cleaning, normalization, and stemming. Furthermore, this research addresses the issue of class imbalance, where negative comments dominated (73.9%) by applying the Random Oversampling (ROS) technique to the training data. The feature extraction was performed using TF-IDF. The experimental results demonstrate that the proposed model achieved an overall Accuracy of 87.22%. Detailed evaluation shows a Precision of 0.91 and Recall of 0.93 for the negative class, confirming the model's robustness. These findings indicate that the majority of public sentiment is critical of the RUU KUHAP, focusing on issues of corruption and trust. This research contributes to the field of text mining by demonstrating the effectiveness of oversampling in improving Naïve Bayes performance on imbalanced social media data.

Keywords: *Sentiment Analysis, RUU KUHAP, Naïve Bayes, TF-IDF, Random Oversampling, Text Mining.*

1. Introduction

The House of Representatives of the Republic of Indonesia (DPR RI) holds a strategic function within the national legislative system. However, the performance of this institution often triggers public polemics. The development of democracy in the digital era is a phenomenon that presents new dynamics in the global political process[1]. This has been clearly evident recently, where the ratification of the Draft Criminal Procedure Code (RUU KUHAP) in 2025 became a heated topic of discussion, raising various controversies regarding the transparency and urgency of the legislation.

In this digital era, public dissatisfaction and aspirations are no longer expressed solely through conventional demonstrations but have shifted to social media platforms. Social media plays a larger role than merely being a source of information; it serves as a space for communication with internal circles that is intimate in nature, as well as a discussion space that is public in nature[2]. This shift aligns with the findings of Ayres (1999), who was the first researcher to analyze the potential use of the internet as a way to change the dynamics of protest, utilizing this channel as a means to disseminate content and organize street protests[3]. This phenomenon confirms that public participation currently relies heavily on cyberspace.

In the context of digital platforms, among the existing social networks such as Flickr and Picasa, YouTube remains the largest video-sharing platform on the Internet[4]. YouTube has become a primary medium for the public to access news and express opinions through the comments column. YouTube users can respond to existing videos, meaning that the greater the usage of YouTube, the more it produces data of very large size[5]. These comments contain valuable information regarding public sentiment towards the government; yet, their unstructured nature and massive volume make manual analysis inefficient and prone to subjectivity. Therefore, a computational approach such as sentiment analysis is required to extract meaningful insights.

Several previous studies have conducted sentiment analysis on government performance and legislation. For instance, a study titled "Analisis Sentimen Kinerja Dewan Perwakilan Rakyat (DPR) pada Twitter Menggunakan Metode Naive Bayes Classifier" has highlighted public perception on microblogging platforms[6]. Additionally, another study regarding "Klasifikasi Sentimen Masyarakat Terhadap Revisi Undang-Undang Tentara Nasional Indonesia Menggunakan Naïve Bayes Classifier" also demonstrated the effectiveness of this algorithm in dissecting legal opinions[7].

However, the majority of these studies predominantly utilized datasets from Twitter or Instagram, focused on older legislative periods, which may not accurately reflect the current socio-political dynamics, particularly regarding the RUU KUHAP 2025 issue. Furthermore, research specifically targeting the 2025 legislative controversies on video-based platforms like YouTube remains limited, despite the platform's ability to facilitate deeper arguments compared to microblogging sites.

Addressing this gap, this study focuses on analyzing public sentiment towards the performance of the DPR regarding the RUU KUHAP controversy using the Naïve Bayes classifier. This algorithm was selected for its proven effectiveness in text classification tasks, particularly due to its computational efficiency and high accuracy in handling high-dimensional data. The primary contribution of this research lies in the recency and specificity of the dataset used, namely 2,370 comment data points collected in 2025, to provide a quantitative measurement of how the public evaluates the legislative body's performance.

2. Research method

This study employs a quantitative approach utilizing text mining techniques to analyze public sentiment. The systematic stages of the research are illustrated in Figure 1, comprising data collection, pre-processing, labeling, modeling, and evaluation. Each stage is designed to ensure the reliability and validity of the final classification results.

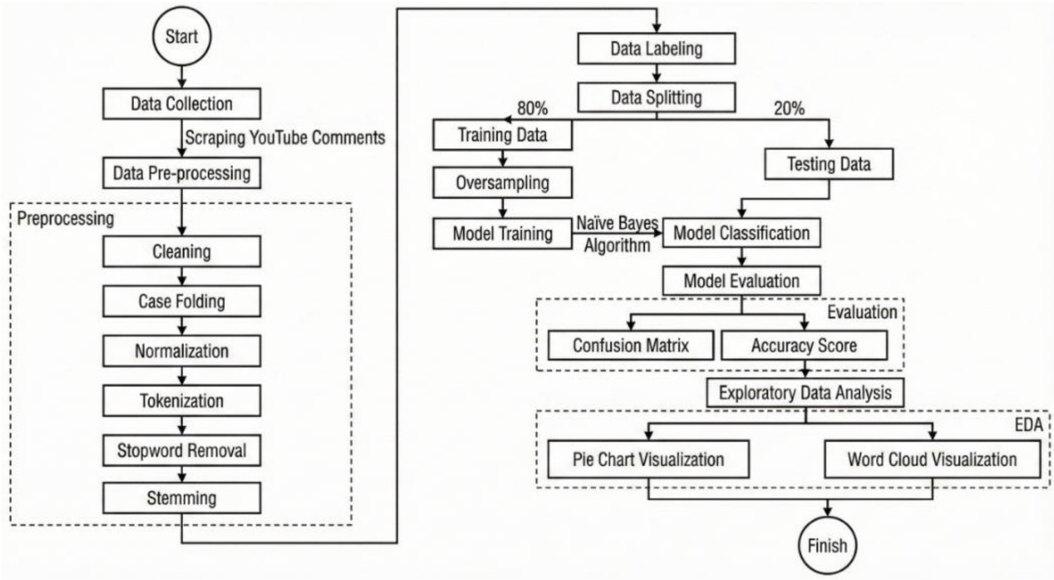

Fig. 1: Process

2.1. Data collection

The dataset used in this study consists of public comments retrieved from YouTube. Web scraping is a data retrieval stage that acts as a dataset collector, serving as the first step of this research[8]. The process targeted videos related to the performance of the Indonesian House of Representatives (DPR) and the RUU KUHAP controversy in 2025. Web scraping serves as an efficient method for extracting large volumes of unstructured data from social media platforms for academic research purposes. The data acquisition was executed using the Python programming language within the Google Colab environment. Specifically, this study utilized the YouTube Data API v3 accessed via the google-api-python-client library to ensure efficient and structured data extraction. This process yielded a total of approximately 2,370 raw comments which were then stored in CSV format for further processing.

2.2. Pre-processing

Raw data derived from social media platforms is typically unstructured and contains significant noise which can degrade classification performance. Therefore, pre-processing is essential to ensure the quality of the input data. As shown in the flowchart, this stage involves six sequential steps.

2.2.1. Cleaning

The first stage, cleaning, focuses on removing non-textual elements and noise from the dataset. User comments on YouTube often contain components that are irrelevant to sentiment classification, such as Uniform Resource Locators (URLs), usernames (mentions), hashtags, numbers, and punctuation marks. Additionally, emojis and special characters are removed to reduce the dimensionality of the feature space without losing significant semantic meaning.

2.2.2. Case folding

Case folding is the process of converting all characters in the document to a uniform letter case, specifically lowercase. This step is crucial to ensure that the machine treats words like "DPR," "Dpr," and "dpr" as the same token. By eliminating case sensitivity, the consistency of the data is maintained, preventing the duplication of identical features in the vector space model.

2.2.2. Normalization

Indonesian comments on social media are characterized by the frequent use of non-standard language, slang, abbreviations, and informal spelling. Normalization aims to convert these non-standard terms into their formal Indonesian equivalents based on a pre-defined dictionary or lexicon. For instance, abbreviations such as "yg" are converted to "yang" and "gk" to "tidak." This process is vital to maximize the effectiveness of the subsequent stemming phase and ensuring the algorithm correctly interprets the sentiment context.

2.2.3. Tokenization

Tokenization is the process of breaking down the stream of text into smaller units called tokens. In this study, the sentences are split into individual words using white space as the delimiter. This step transforms the text strings into a list of words, which serves as the fundamental unit for frequency analysis in the Naïve Bayes classifier.

2.2.4. Stopword removal

Stopwords are common words that appear frequently in a language but carry little to no sentiment information, such as conjunctions ("dan", "atau"), prepositions ("di", "ke"), and pronouns. Removing these words is necessary to focus the analysis on content-bearing words (adjectives, verbs, and nouns) that significantly contribute to the sentiment polarity. This study utilizes a standard Indonesian stopword list to filter out these irrelevant tokens.

2.2.5. Stemming

he final step in pre-processing is stemming, which involves reducing words to their root or base form by removing prefixes, suffixes, infixes, and confixes. For Indonesian text, this stage employs the Sastrawi library to perform text processing based on the Indonesian language[9]. This library implements the Nazief and Adriani algorithm, ensuring that words with similar meanings are grouped into a single feature.

2.3. Labeling and spitting

Following the cleaning process, the data was labeled into sentiment classes to serve as ground truth. The labeled dataset was then split into two subsets comprising training data and testing data. Aside from parameters and data splitting, another necessary step is to balance the data by using the Random Oversampling (ROS) technique[10]. Oversampling helps to adjust the class distribution, ensuring that the model learns effectively from the minority class and preventing bias towards the majority class.

2.4. Classification and evaluation

Before classification, the textual data is converted into numerical vectors. The main objective of the TF-IDF method is to evaluate the importance of a word (term) in a document within the context of a larger document collection[11]. Once the features are extracted, the classification is performed using the Naïve Bayes algorithm. Naïve Bayes is a probability calculation utilized as a classification method. This model is easy to construct and not complicated, making it considered appropriate for databases ranging from small to large sizes[12]. This probabilistic classifier applies Bayes' theorem with the assumption of independence between features.

2.5. Exploratory data analysis (EDA)

To provide a comprehensive visualization of the results, Exploratory Data Analysis was conducted. Exploratory Data Analysis (EDA) is a method or procedure for examining data with the aim of identifying existing characteristics and trends[13]. Visualization techniques are vital in text mining to reveal these underlying patterns and distributions within the data. The output includes a Pie Chart to depict the proportion of positive and negative sentiments, and a Word Cloud to visualize the most frequent terms appearing in the public comments regarding the DPR

3. Result and discussion

This section presents the experimental results of the sentiment analysis conducted on the performance of the DPR regarding the RUU KUHAP controversy. The discussion covers the data characteristics, the outcome of the pre-processing stages, and the evaluation of the Naïve Bayes classification model.

3.1. Data collection

The data acquisition process was carried out using a scraping script tailored for the YouTube platform. As described in the methodology, the target data focused on videos discussing the ratification of the RUU KUHAP in 2025. This process successfully yielded a total of 2,370 data. The raw dataset consists of six attributes: video_title, video_id, author, text, likes, and published_at.

Among these attributes, the text column serves as the primary feature for sentiment extraction, containing the actual arguments and opinions of the public. A sample of the raw dataset structure obtained from the scraping process is presented in Table 1.

Tabel 1: Dataset

video_title	Video_id	author	text	likes	Published_at
Mengapa DPR Ngotot Mengesahkan RUU KUHAP	RnkvaiS2ZqQ	@dhiraanantawijaya3983	Gw demen DPR, totalitas!... Klo molor, molooooorrrr bgt bisa tahunan..	0	2025-11-21T07:55:56Z
[FULL] Jelang Disahkan DPR, YLBHI …	zzcphkiu2tk	@RipaiIdoy	GK usah bayar pajak buat masyarakat indonesia,,mereka juga dan negara ini tanpa rakyat…	0	2025-11-21T05:56:09Z
BREAKING NEWS - Demo Mahasiswa di DPR…	ce4hxUh5gQg	@NurpitriUviet-s1p	Kami rakyat Indonesia mendukung dan mendoakan adik2 mahasiswa	0	2025-11-21T09:06:06Z
[FULL] Ketua Komisi III Habiburokhman…	zX1w17T4s7o	@ryanal8409	Di suruh nanya, satu pertanyaan udah selesai. Jawab nya gitu lagi	0	2025-11-20T04:33:26Z
DPR: Roy Suryo Korban KUHP Orde Baruâ—	4Kb8Ohyr65Q	@muchammadmuzayyin9259	Kok Orde baru, trs kerja kalian ngapain...	0	2025-11-20T21:56:39Z

The raw data shown in Table 1 indicates that the text is still unstructured, containing usernames, varying capitalization, and potential noise, which confirms the necessity of the subsequent pre-processing stage.

3.2. Data pre-processing

After the data collection phase, the raw text underwent a series of pre-processing steps to improve data quality and reduce noise. This stage is critical as the raw comments from YouTube contained various irregularities. Table 2 illustrates the step-by-step transformation of a sample comment from the dataset, demonstrating how a complex sentence is reduced to its essential features.

Table 2: Pre-processing

Stage	Result
Raw Data	"Ayo siapa yg seharusnya berhak membubarkan DPR, kok masih saja di biarkan, akibatnya pekerjaannya yg dihasilkan tidak pro rakyat, dan hanya sekedar saja tidak berbobot"
Cleaning	"Ayo siapa yg seharusnya berhak membubarkan DPR kok masih saja di biarkan akibatnya pekerjaannya yg dihasilkan tidak pro rakyat dan hanya sekedar saja tidak berbobot"
Case Folding	"ayo siapa yg seharusnya berhak membubarkan dpr kok masih saja di biarkan akibatnya pekerjaannya yg dihasilkan tidak pro rakyat dan hanya sekedar saja tidak berbobot"
Normalization	"ayo siapa yang seharusnya berhak membubarkan dpr kok masih saja di biarkan akibatnya pekerjaannya yang dihasilkan tidak pro rakyat dan hanya sekadar saja tidak berbobot"
Tokenization	['ayo', 'siapa', 'yang', 'seharusnya', 'berhak', 'membubarkan', 'dpr', 'kok', 'masih', 'saja', 'di', 'biarkan', 'akibatnya', 'pekerjaannya', 'yang', 'dihasilkan', 'tidak', 'pro', 'rakyat', 'dan', 'hanya', 'sekadar', 'saja', 'tidak', 'berbobot']
Stopword Removal	['berhak', 'membubarkan', 'dpr', 'biarkan', 'akibatnya', 'pekerjaannya', 'dihasilkan', 'pro', 'rakyat', 'sekadar', 'berbobot']
Stemming	['hak', 'bubar', 'dpr', 'biar', 'akibat', 'kerja', 'hasil', 'pro', 'rakyat', 'kadar', 'bobot'] |

As shown in Table 2, the pre-processing pipeline significantly reduced the complexity of the data. The Cleaning stage successfully removed punctuation marks (commas) and excessive whitespace. Normalization corrected non-standard abbreviations such as "*yg*" to "*yang*" and "*sekedar*" to "*sekadar*". Furthermore, Stopword Removal eliminated frequent but insignificant words like "*ayo*", "*siapa*", and "*tidak*", leaving only content-bearing terms. Finally, Stemming reduced the words to their root forms, such as "*membubarkan*" becoming "*bubar*" and "*pekerjaannya*" becoming "*kerja*". This process transforms the unstructured sentence into a concise list of keywords that represent the core sentiment of the comment, which is then ready for the labeling and classification process.

3.3. Data labeling

The cleaned data was subsequently subjected to a labeling process to determine the ground truth for classification. This study utilized a lexicon-based approach with a weighted scoring system. In this mechanism, specific words are assigned positive or negative weights. The sentiment of a comment is determined by calculating the cumulative score of the terms it contains; a positive total score indicates a positive sentiment, while a negative total score indicates a negative sentiment.

The distribution of the labeled data is visualized in Table 3.

Table 3: Labeling

Positive	Negative
kalau memang benar asli tunjuk adil buka sesua...	orang pinter ngeri cerdik licik suka masuk sel…
semangat adil anak ku indonesia cerdas hebat	asal masuk rakyat wk wk wk rakyat mana brooo j…
wapres baik grr	baik apa cerdas apa orang pdip sandiwara pedoman
bakat suara top sangat buat mau hoki top cobai…	percaya lah kata ku kalo nama pimpin raja pers…
rakyat mana dulu buat undang pro rakyat	salah jangan minta maaf tegur anggota dewan

As illustrated in Table 3, the dataset reveals a significant disparity in public opinion. The Negative sentiment is overwhelmingly dominant, accounting for 73.9% (approximately 838 comments) of the total dataset. In contrast, the Positive sentiment comprises only 26.1% (approximately 296 comments).

This distribution empirically demonstrates the high level of public dissatisfaction with the performance of the DPR regarding the RUU KUHAP controversy in 2025. From a machine learning perspective, this dataset exhibits a class imbalance problem. The ratio between the majority class (negative) and the minority class (positive) is nearly 3:1. This finding justifies the necessity of the Oversampling technique mentioned in the research methodology section. Without balancing the data, the Naïve Bayes model would likely develop a bias towards the negative class, potentially ignoring the patterns within the positive class.

3.4. Feature extraction and data balancing

Before the classification process, the textual data was transformed into a numerical representation using the Term Frequency-Inverse Document Frequency (TF-IDF) weighting method. This technique evaluates how relevant a word is to a document in a collection. The TF-IDF weight is calculated using the formula shown in (1):

$$W(t,d) = TF(t,d) \times IDF(t) \tag{1}$$

Where:

TF(t,d) (Term Frequency): Measures how often a term *t* appears in a document *d*.

$$TF(t,d) = \frac{Number\ of\ occurrences\ of\ term\ t\ in\ document\ d}{Total\ number\ of\ words\ in\ document\ d} \tag{2}$$

IDF(t) (Inverse Document Frequency): Measures how unique a term *t* is across the entire corpus (all documents).

$$IDF(t) = log\left(\frac{Total\ number\ of\ documents\ in\ the\ corpus\ (N)}{Number\ of\ documents\ containing\ term\ (df_t)}\right) \tag{3}$$

In this study, the “TfidfVectorizer” was configured with a maximum feature limit of 2,000 to focus on the most significant terms and reduce computational complexity.

Following feature extraction, the dataset was split into training and testing sets with a ratio of 80:20. It is important to note that the data splitting was performed prior to the oversampling process. This sequence is strictly maintained to ensure that the testing data remains pure, thereby preventing data leakage. Upon splitting, the initial distribution of the training set exhibited a severe imbalance (663 Negative vs. 244 Positive).

To address this, the Random Oversampling (ROS) technique was applied to the training set, resulting in a balanced distribution (663 samples for each class). This balanced dataset was subsequently used to train the Multinomial Naïve Bayes classifier. The algorithm predicts the sentiment class c for a given document *x* based on the Maximum A Posteriori (MAP) estimation defined in (4):

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \tag{4}$$

In this equation, $P(c|x)$ is the posterior probability of class *c* (positive or negative) given the document *x*. $P(x|c)$ is the likelihood which represents the probability of the document appearing in class *c*, *P*(*c*) is the prior probability of the class, and *P*(*x*) is the predictor prior probability. By maximizing this probability, the model determines the most suitable sentiment label for the unobserved data.

3.5. Model evaluation result

The performance of the Naïve Bayes classifier was evaluated using the unseen testing dataset, consisting of 227 samples. The evaluation is primarily based on the Confusion Matrix, which maps the comparison between the actual labels and the predicted labels produced by the model. The confusion matrix generated from the experiment is presented in Figure 1.

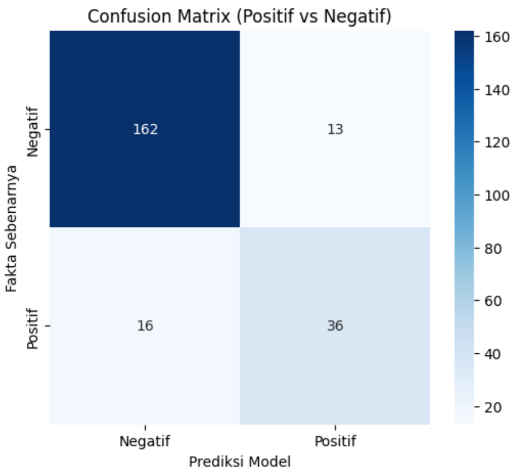

Fig. 1: Confussion Matrix

Based on Figure 1, the model correctly identified 162 comments as Negative and 36 comments as Positive. However, there were misclassifications, where 16 positive comments were predicted as negative and 13 negative comments were incorrectly predicted as positive.

To quantitatively measure the performance, the standard metrics of Accuracy, Precision, and Recall were calculated. Accuracy represents the ratio of correctly predicted observations to the total observations, calculated using equation (5):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{36 + 162}{36 + 162 + 13 + 16} = \frac{198}{227} = 0.87 \quad (5)$$

Precision measures the ratio of correctly predicted positive observations to the total predicted positive observations, as shown in (6):

$$Precision = \frac{TN}{TN + FN} = \frac{162}{162 + 16} = \frac{162}{178} = 0.91 \quad (6)$$

Recall (Sensitivity) measures the ratio of correctly predicted positive observations to the all observations in actual class, as defined in (7):

$$Recall = \frac{TN}{TN + FP} = \frac{162}{162 + 13} = \frac{162}{175} = 0.93 \quad (7)$$

Table 4 summarizes the detailed classification report derived from these formulas.

Table 4: Evaluation

	Precision	Recall	F1-score	Support
Negative	0.91	0.93	0.92	175
Positive	0.73	0.69	0.71	52
Accuracy			0.87	227
Macro Avg	0.82	0.81	0.82	227
Weighted Avg	0.87	0.87	0.87	227

As demonstrated in Table 4, the proposed Naïve Bayes model achieved a high Overall Accuracy of 87%. This indicates that the model correctly predicted the sentiment for approximately 87 out of every 100 comments in the test set.

A detailed analysis of each class reveals robust performance, particularly for the Negative class, which achieved a Precision of 0.91 and a Recall of 0.93. This high recall score implies that the model is extremely capable of detecting negative public sentiment.

For the Positive class, the model achieved a Precision of 0.73 and a Recall of 0.69. Although these scores are slightly lower than those of the negative class, they are statistically significant given the complexity of the text data. The F1-Score of 0.71 for the positive class confirms that the model maintains a good balance between precision and recall, proving that the Oversampling technique was effective in helping the model learn the minority class patterns without overfitting.

The Macro Average F1-Score of 0.82 further validates the model's stability across different classes, indicating that the high accuracy is not merely a result of predicting the majority class, but rather a reflection of genuine learning capability.

3.6. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was conducted to gain deeper insights into the characteristics of the public opinion regarding the DPR and RUU KUHAP. This section analyzes the distribution of sentiments and examines the semantic patterns of words that frequently appear in each sentiment class.

3.6.1. Sentiment distribution analysis

Based on the labeling results using the weighted scoring system, a visualization of the sentiment proportion was generated. Figure 2 illustrates the comparison between positive and negative sentiments within the dataset.

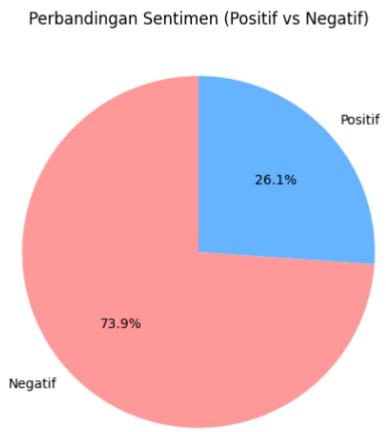

Fig. 2: Pie Chart

As shown in Figure 2, the dataset is dominated by Negative sentiment (73.9%), whereas Positive sentiment accounts for only 26.1%. This significant disparity indicates a strong tendency of public dissatisfaction. The majority of the comments reflect skepticism, criticism, and rejection of the DPR's performance. The high percentage of negative sentiment aligns with the controversial nature of the RUU KUHAP issue, which has sparked widespread public concern regarding the integrity of the legislative process.

3.6.2. Word cloud analysis

To visually identify the most frequent terms associated with public opinion, this study generated Word Cloud visualizations. In the formation of a Word Cloud, words that appear more frequently are displayed larger, creating a visual representation that provides an overview of the most common or dominant words in a specific context[14].

The analysis begins with the negative sentiment, which constitutes the majority of the dataset. As illustrated in Figure 3, the negative discourse is heavily dominated by emotionally charged keywords such as "korupsi" (corruption), "jahat" (evil), "bohong" (lie), and "tikus" (common metaphor for corruptors). The prominent appearance of the word "bubar" (disband) alongside "Dewan" suggests a strong and aggressive public demand to dissolve the legislative body due to a profound lack of trust. These terms confirm that the negative sentiment is driven not just by disagreement with the bill, but by a deeper moral criticism of the council members' integrity.

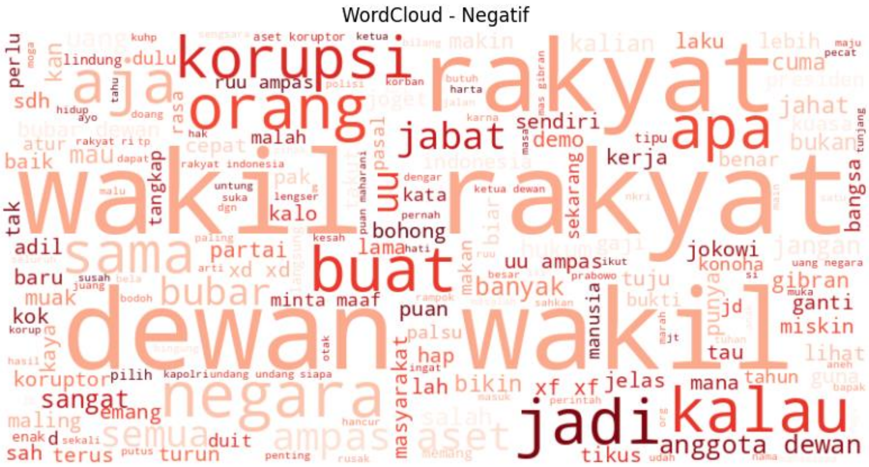

Fig. 3: Negative Wordcloud

In stark contrast to the aggressive tone of the negative comments, the positive sentiment reveals a more constructive and supportive lexicon, as presented in Figure 4. Dominant terms in this category include "dukung" (support), "benar" (correct), "maju" (forward), and "hukum" (law). Interestingly, specific names and honorifics such as "Gibran" and "Pak" appear frequently in the positive cloud. This indicates that the positive sentiment is often directed towards specific political figures or individual leaders whom the public trusts, rather than the legislative institution as a whole. The presence of the word "adil" (fair) further reflects a segment of the public that retains hope for a just legal system under the current administration.

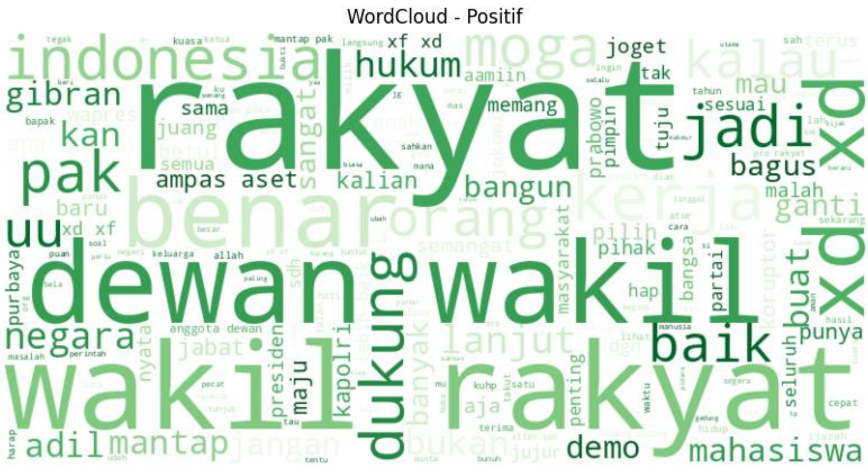

Fig. 4: Positive Wordcloud

When analyzing the dataset as a whole in Figure 7, the underlying narrative of the controversy becomes clear. The combined visualization highlights that the words "Rakyat" (People), "Dewan" (Council), and "Wakil" (Representative) are the central subjects of discussion across both sentiments. This implies that the core issue revolves around the strained relationship between the people and their representatives. While the subjects are the same, the context differs significantly: the negative class associates "Dewan" with failure and corruption, whereas the positive class associates specific "Wakil" or leaders with progress. This visual analysis corroborates the statistical findings that the RUU KUHAP issue has created a polarized yet predominantly critical public discourse.

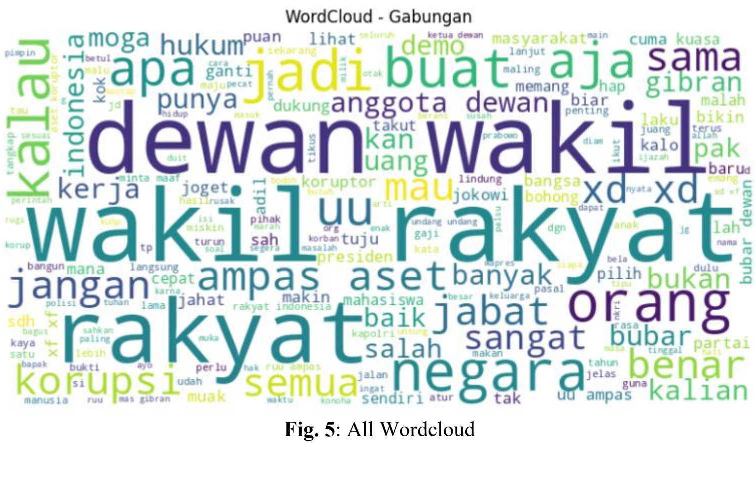

Fig. 5: All Wordcloud

4. Conclusion

This study has successfully implemented a sentiment analysis system to classify public opinion regarding the ratification of the RUU KUHAP 2025 using the Naïve Bayes algorithm. Based on the experimental results and analysis, several key conclusions can be drawn.

First, the public sentiment on YouTube is predominantly Negative (73.9%), reflecting widespread dissatisfaction and skepticism towards the DPR's performance. The Word Cloud analysis reveals that this negativity is driven by issues of trust and corruption, characterized by keywords such as *"korupsi"* and *"tikus"*. Conversely, the Positive sentiment (26.1%) is significantly smaller and primarily focuses on support for specific political figures rather than the legislative body itself.

Second, the proposed methodology demonstrated robust performance. The application of Random Oversampling (ROS) proved to be highly effective in handling the class imbalance problem. By balancing the training data, the Multinomial Naïve Bayes classifier, combined with TF-IDF feature extraction, achieved an impressive overall Accuracy of 87.22%. The model exhibited a high Recall of 0.93 for the negative class and a respectable F1-Score of 0.71 for the positive class, indicating that the system is reliable in detecting both criticism and support.

For future research, it is recommended to expand the dataset sources to include other platforms such as X (formerly Twitter) or Instagram to gain a more comprehensive demographic view. Additionally, comparing the performance of Naïve Bayes with deep learning models like Long Short-Term Memory (LSTM) or BERT (Bidirectional Encoder Representations from Transformers) could potentially yield even higher accuracy in handling Indonesian slang and context.

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