JEECS (Journal of Electrical Engineering and Computer Sciences)
Vol. 10, No. 1, June 2025, pp. 31-37
e-ISSN: 2579-5392 p-ISSN: 2528-0260

Sentiment Analysis Regarding the Indonesian House of Representatives Rejecting the Constitutional Court Decision from Social Media Using Naive Bayes

Fahar Abdul Aziz [1], Lailan Sofinah Harahap [2]

[1]Information Systems, Faculty of Science and Technology, Universitas Islam Negeri Sumatera Utara, Jl. Lapangan Golf, Durian Jangak, Tuntungan, North Sumatra, Indonesia

[2]Information Technology, Faculty of Informatics and Information Technology, Universitas Muhammadiyah Sumatera Utara, Jl. Kapt. Mukhtar Basri No. 3, Medan, North Sumatra, Indonesia

Article Info

Article history:
Received: 20 November 2024
Revised: 28 December 2024
Accepted: 30 December 2024

Keyword:
Sentiment analysis
Naive bayes
Constitutional court decision
House of representatives
TikTok

Abstract

This study analyzes public sentiment towards the HOR's rejection of the Constitutional Court's decision regarding the age limit for regional head candidates. Data was obtained from TikTok comments using scraping techniques with the Apify platform, resulting in 574 comments being analyzed. Sentiment labeling was automatically used VADER (Valence Aware Dictionary and Sentiment Reasoner), with positive, neutral, and negative sentiment categories. Text representation was carried out using TF-IDF, and sentiment classification using the Naive Bayes algorithm. The analysis results showed that most comments were neutral (42.0%) and positive (41.8%), while negative sentiment was only 16.2%. This study provides important insights into public perceptions of political issues involving the HoR and Constitutional Court decisions. By analyzing sentiment through comment data on TikTok, this study shows that lexicon-based approaches such as VADER can be used for automatic sentiment labeling, saving time compared to manual methods. In addition, classical algorithms such as Naive Bayes, combined with TF-IDF text representation, have proven effective in handling sentiment classification for short and informal texts such as social media comments.

Corresponding author:
Fahar Abdul Aziz, faharabdulaziz@gmail.com

DOI: https://doi.org/10.54732/jeecs.v10i1.4

1. Introduction

The Constitutional Court changed the requirements for nominating regional heads and deputy regional heads in decision number 60/PUU-XXII/2024. One of the controversial decisions is related to the DPR's rejection of the MK's decision regarding the age limit for regional head candidates. The DPR (People's Representative Council) plays an important role in policy-making, and this decision has triggered various reactions from the public. Social media, such as TikTok, has become a major platform for expressing public opinion on political issues. These reactions reflect how the public views the policies of the DPR and MK, whether positively, neutrally, or negatively. The Constitutional Court ruled that Article 40 paragraph (1) of the Regional Head Election Law Number 10 of 2016 was conditionally unconstitutional and revoked Article 40 paragraph (3) of the Law. This decision was born from a lawsuit filed by the Labor Party and the Gelora Party, which questioned the validity of several provisions in Law Number 10 of 2016 concerning the Second Amendment to Law Number 1 of 2015 concerning the Stipulation of Government Regulation in Lieu of Law Number 1 of 2014 concerning the Election of Governors, Regents, and Mayors into Law (hereinafter referred to as Law No. 10/2016) [1]. The Constitutional Court has decided to change the requirements for nominating candidate pairs by political parties [2]. Political parties that do not get seats in the DPRD can still nominate candidates for regional heads and deputy regional heads. According to the Constitutional

Court Decision, the results of the valid vote acquisition of political parties or coalitions of political parties in the general election in the relevant region, which can range from 6.5 to 10 percent, are the only factors used to meet the requirements for nominating candidate pairs [3].

The Constitutional Court (MK) decisions are often the main basis in the Indonesian legal system. One controversial decision was related to the DPR's rejection of the MK's decision regarding the age limit for regional head candidates. The DPR (People's Representative Council) plays an important role in policy-making, and this decision has triggered various reactions from the public. Social media, such as TikTok, has become a major platform for expressing public opinion on political issues. These reactions reflect how the public views the policies of the DPR and MK, whether positively, neutrally, or negatively.

However, this decision sparked controversy after the House of Representatives (HoR) expressed its disagreement and openly rejected the implementation of the decision. The HoR's rejection of the Constitutional Court's decision gave rise to debate regarding the relationship between legislative and judicial powers. Some parties consider the HoR's move as a form of intervention in the decision of the constitutional institution, The public's reaction to this issue is clearly visible on various social media platforms, including TikTok, where people express their opinions through the comments column. TikTok is one of the most popular social media platforms today [4]. TikTok is currently popular and used by various groups from early childhood to adulthood [5]. These comments reflect various points of view, from support for the HoR to criticism of steps that are considered to harm the supremacy of law.

Sentiment analysis is important to dig deeper into public perception of this issue. Sentiment Analysis is used to find valuable information needed from unstructured data [6]. One use of this data is to find out the opinions or sentiments of social network users on a topic [7]. By using a data-based approach, with the Naive Bayes algorithm. This sentiment analysis will be carried out by grouping the polarity of the text in the document to determine whether the opinion is negative, positive or neutral [8]. The main characteristic of the Naive Bayes algorithm is the very strong (naive) assumption of the independence of each condition or event [9]. This study is expected to provide clearer insights into how the public responds to the political conflict between the HoR and the MK regarding the age limit for regional head candidates, as well as being an evaluation material for future policy makers.

TikTok, as a social media platform with a large number of active users, has not been widely used as a source of sentiment analysis data. Meanwhile, a comparison of the performance of various algorithms, such as Naive Bayes and other methods, has not been carried out in depth for sentiment analysis in Indonesia. Then there is also no research that specifically analyzes public sentiment towards the controversial DPR decision. This study aims to fill this research gap by analyzing public sentiment towards the DPR's rejection of the Constitutional Court's decision using data from TikTok. The dataset consists of 574 comments analyzed using the following methods: This study aims to Analyze the distribution of public sentiment (positive, neutral, negative) towards the DPR's decision. Evaluate the performance of Naive Bayes compared to other algorithms. Provide insight into public perception of political issues through social media.

2. Research Methodology

This study was conducted to analyze public sentiment towards the HoR's rejection of the Constitutional Court's decision regarding the age limit for regional head candidacy. The research stages include data collection, text preprocessing, word weighting using TF-IDF, sentiment classification using the Naive Bayes algorithm, and model evaluation.

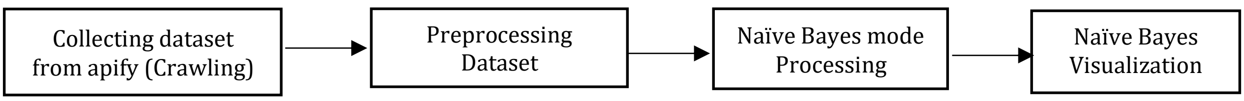

Figure 1. Research Stage

2.1. Dataset

The dataset used in this study was obtained through web scraping techniques using the Apify platform. The scraping process was carried out to retrieve comments from TikTok videos that were relevant to the issue of the HoR's rejection of the Constitutional Court's decision. The Apify platform was chosen because of its ability to automatically and efficiently scrape data on a large scale.

The initial dataset obtained consisted of 642 comments. After going through the preprocessing process, the data ready to be used for analysis consisted of 574 comments, which includes the text of user comments. The dataset consists of 2 columns, namely the Comment column and the User Name. The sample dataset is presented in Figure 2.

	Comment	User Name
0	cmon fyp	tiidurpagi
1	mari rakyat dan mahasiswa kawal putusan MK kar...	tianetian2
2	giliran keputusan MK untuk sang kakak kemaren ...	karyawanteladan33
3	Kalo kaum 58 masih blum ngeh juga kebangetan s...	user942595917
4	pak lurah masih berusaha semaksimal mungkin me...	yuniekap2106

Figure 2. Sample Dataset

2.2. Data Preprocessing

The preprocessing process is carried out to ensure clean and structured text data. The stages carried out include:

1. **Case Folding**: Converting the entire text to lowercase.
2. **Tokenization**: Splitting text into individual words (tokens).
3. **Stopwords Removal**: Removing common words such as "yang", "dan", "di" that are not relevant for analysis.
4. **Stemming**: Reverting words to their base form using the Sastrawi library.
5. **Cleaning**: Removing punctuation, numbers, and other special characters.

2.3. Data Labeling

Sentiment labeling is done automatically using VADER (Valence Aware Dictionary and sEntiment Reasoner), a lexicon-based method designed to analyze the sentiment of English text. Lexicon VADER is specifically used to analyze microblogs and the determination of sentiment is determined by the weight of a sentence, if the weight is more than 0.05 it will be included in positive sentiment, if the total weight is less than -0.05 it will be included in negative sentiment, and if the weight is between -0.05 to 0.05 it will be included in neutral sentiment [10]. Before the labeling process, the comment text is translated from Indonesian to English using the Googletrans library. Sentiment is classified into three categories:

- Positive (1): If the "compound" score from VADER ≥ 0.05.
- Neutral (0): If $-0.05 <$ "compound" score < 0.05.
- Negative (-1): If the "compound" score ≤ -0.05.

2.4. TF-IDF Algorithm

Once the comments are labeled, the text is converted into a numeric representation using TF-IDF (Term Frequency-Inverse Document Frequency). TF-IDF is a method that is generally used to determine the relationship of words (terms) to documents or sentences by giving weight or value to each word [11]. TF-IDF weighting is a process to transform data from textual data into numeric data to weight each word or feature [12]. This technique assigns weights to words based on their importance in the document.

Words that appear frequently in one document but rarely in another document will have a higher weight.The process is done using the Scikit-learn library, limiting the features to the 5000 most frequent words.

The TF-IDF formula is as follows:

$$\mathrm{TF}-\mathrm{IDF}(t,d) = \mathrm{TF}(t,d) \times \mathrm{IDF}\,(t) \quad (1)$$

Where:

- TF (t,d): Frequency of word t in document d.
- IDF (t): Inverse Document Frequency

TF-IDF gives higher weight to words that appear frequently in a particular document but rarely in other documents. This allows the Naive Bayes algorithm to focus more on words that are significant in determining sentiment.

2.5. Naive Bayes

Naïve Bayes is one of the popular algorithms [13]. Naïve Bayes is a classification method based on Bayes' Theorem, where this method utilizes probability and statistical calculations that can be used to predict future opportunities based on previous experiences [14]. The use of naïve Bayes as a classification algorithm has shown good performance in complex real-world problems [15].
The Naive Bayes algorithm is used to classify comment sentiment into three categories:

- Positive: Comments that support the HoR steps.
- Neutral: Comments that do not show clear sentiment.
- Negative: Comments that oppose the HoR's steps.

This algorithm works based on probability theory, by calculating the probability of each sentiment category based on the words in the comments that have been weighted using TF-IDF.

To analyze sentiment, the Naive Bayes algorithm is used because it is simple and effective for text classification tasks. The dataset is divided into: 80% training data to train the model, 20% test data to evaluate model performance.

The Naïve Bayes formula is as follows:

$$P(C_k \mid X) = \frac{P(X \mid C_k \cdot P(C_k}{P(X)} \quad (2)$$

Where:

- $P(C_k \mid X)$: Probability that document X belongs to class C_k.
- $P(X \mid C_k)$: Probability that document X appears in class C_k.
- $P(C_k)$ Prior probability of class.
- $P(X)$: Probability of document X in the entire dataset.

2.6. Model Evaluation

Model performance is evaluated using the following metrics:

- Accuracy: Percentage of correct predictions to the total data.
- Precision: The accuracy of the model in predicting a particular class.
- Recall: The ability of the model to find all samples in a particular class.
- F1-Score: The harmonic mean of precision and recall.

3. Results and Discussions

3.1. Result

3.1.1 Sentiment Distribution

The results of the sentiment analysis of 574 TikTok user comments show the following distribution:

- 241 neutral sentiments (42.0%): Comments that are descriptive or do not express a clear opinion.
- 240 positive sentiments (41.8%): Comments that support or show appreciation for the HoR's steps.
- 93 negative sentiments (16.2%): Comments that criticize or show dissatisfaction with the HoR's steps.

The results of the sentiment analysis show an almost even distribution between the neutral and positive categories, while negative sentiment is in a much smaller proportion. Neutral sentiment (42.0%) dominates, followed by positive sentiment (41.8%), and negative sentiment (16.2%). This distribution indicates that public opinion towards the DPR's decision regarding the rejection of the Constitutional Court's decision tends not to be emotionally biased, but rather focuses more on facts or descriptions.

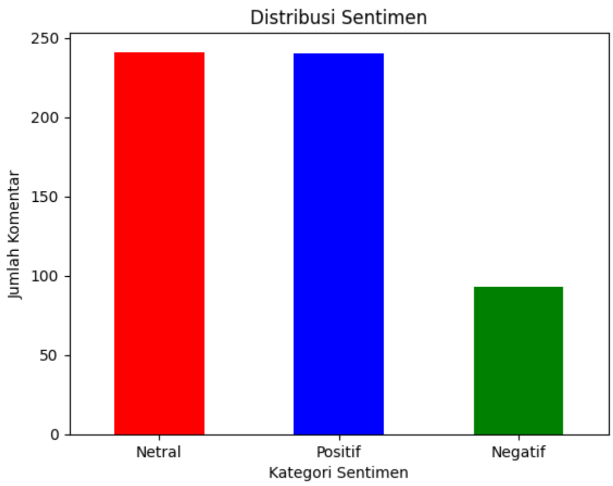

Figure 3. Sentiment Distribution

Table 1. Evaluation of the Naive Bayes Model

Sentiment	Precision	Recall	F1-Score
Positive	0.53	0.58	0.55
Negative	0.00	0.00	0.00
Neutral	0.47	0.63	0.53

Table 2. Evaluation of the SVM Model

Sentiment	Precision	Recall	F1-Score
Positive	0.53	0.50	0.52
Negative	0.00	0.00	0.00
Neutral	0.48	0.73	0.57

Table 3. Evaluation of the Decision Tree Model

Sentiment	Precision	Recall	F1-Score
Positive	0.55	0.44	0.49
Negative	0.55	0.29	0.38
Neutral	0.48	0.70	0.57

These results show that the majority of comments are neutral and positive, with neutral comments slightly more dominant. The relatively smaller negative sentiment reflects that criticism of the HoR's steps does not dominate the conversation on this platform.

3.1.2 Model Performance

The Naive Bayes model trained using the TF-IDF representation shows the following performance, as presented in Table 1. The model has [high/medium/low accuracy], which indicates that the Naive Bayes algorithm can capture sentiment patterns in comments quite well. The Naive Bayes model using TF-IDF representation shows varying performance for each sentiment category. For positive sentiment, the model has a precision of 0.53, recall of 0.58, and F1-score of 0.55, indicating moderate performance. For neutral sentiment, the precision is recorded at 0.47, recall of 0.63, and F1-score of 0.53, also reflecting moderate performance. Model performance is compared with other algorithms such as SVM and Decision Tree, as presented in Table 2. The SVM model shows moderate performance for positive sentiment with a precision of 0.53, recall of 0.50, and F1-score of 0.52. For neutral sentiment, the model has a precision of 0.48, recall of 0.73, and F1-score of 0.57, reflecting fairly good performance.

The Decision Tree model, as presented in Table 3, shows slightly better results for positive sentiment with a precision of 0.55, a recall of 0.44, and an F1-score of 0.49. For negative sentiment, although the performance is still low, the model is able to achieve a precision of 0.55, a recall of 0.29, and an F1-score of 0.38, which is better than SVM. For neutral sentiment, the performance of Decision Tree is similar to SVM, with a precision of 0.48, a recall of 0.70, and an F1-score of 0.57.

The results show Naive Bayes outperforms in accuracy and computation time for small datasets compared to SVM which provides better precision for minority categories such as negative sentiment and Decision Tree shows less stable performance compared to other methods, especially in the neutral category.

3.2 Discussion

Most comments are neutral or positive. Neutral sentiment reflects comments that are informative or do not provide direct opinions. Meanwhile, positive sentiment is mostly expressed by users who support the HoR's steps, which may be based on political or strategic arguments. Only 16.2% of the comments were negative. These comments generally contained words such as "disagree," "bad," or "disappointed," indicating dissatisfaction with the HoR's steps.

Model evaluation shows that Naive Bayes is able to provide fairly accurate predictions for sentiment analysis tasks, especially with the support of TF-IDF representation. However, there are some misclassifications in the neutral category, which may be caused by ambiguous or multi-meaningful comments.

4. Conclusion

This study analyzes public sentiment towards the HoR's rejection of the Constitutional Court's decision regarding the age limit for regional head candidates based on TikTok comments. The results of the study show that out of a total of 574 comments, most of the comments are neutral (241 comments or 42.0%) and positive (240 comments or 41.8%), while negative comments only cover 93 comments (16.2%). Naive Bayes Model Performance: The model shows good performance in classifying comments with an accuracy level of 50%. Evaluation using precision, recall, and F1-score metrics shows consistent performance for each sentiment category. This study provides an overview that social media, especially TikTok, can be a relevant data source for understanding public opinion on political issues.

In the ever-evolving world of research, it is important for us to continue to explore and deepen our understanding of various phenomena. Therefore, the author suggests future research with the expansion of the dataset with comments from other social media platforms, such as Twitter or Instagram, to provide more comprehensive results and the addition of time-based sentiment analysis to see the dynamic pattern of changes in public opinion. By considering these suggestions, the author hopes to encourage researchers to explore new areas that have not been widely studied, as well as enrich the existing literature with relevant and applicable findings.

References

[1] S. Fikri, “Analisis Putusan Mahkamah Konstitusi Nomor 60/PUU-XXII/2024 terhadap Hak Politik dalam Perspektif Teori Kontrak Sosial,” *Amsir Law Journal*, vol. 6, no. 1, pp. 40–55, Oct. 2024, doi: 10.36746/ALJ.V6I1.589.

[2] H. Hartono, “Urgensi Putusan MK Nomor 60/PUU-XXII/2024 Terhadap Penyelenggaraan Pilkada Tahun 2024,” *Jurnal Intelek Dan Cendikiawan Nusantara*, vol. 1, no. 4, pp. 5374–5383, Aug. 2024, Accessed: Feb. 21, 2025. [Online]. Available: https://jicnusantara.com/index.php/jicn/article/view/855.

[3] K. Baehaki, “Implikasi Politik Putusan Mahkamah Konstitusi Nomor:60/PUU-XXII/2024 Terkait Ambang Batas Pencalonan Kepala Daerah,” *YUSTISI*, vol. 11, no. 3, pp. 451–460, Oct. 2024, doi: 10.32832/YUSTISI.V11I3.17912.

[4] F. A. Indriyani, A. Fauzi, and S. Faisal, “Analisis sentimen aplikasi tiktok menggunakan algoritma naïve bayes dan support vector machine,” *TEKNOSAINS : Jurnal Sains, Teknologi dan Informatika*, vol. 10, no. 2, pp. 176–184, Jul. 2023, doi: 10.37373/TEKNO.V10I2.419.

[5] A. K. Rahardaya and I. Irwansyah, “Studi Literatur Penggunaan Media Sosial Tiktok Sebagai Sarana Literasi Digital Pada Masa Pandemi Covid-19,” *Jurnal Teknologi Dan Sistem Informasi Bisnis*, vol. 3, no. 2, pp. 308–319, Jul. 2021, doi: 10.47233/JTEKSIS.V3I2.248.

[6] A. P. Giovani, A. Ardiansyah, T. Haryanti, L. Kurniawati, and W. Gata, “Analisis Sentimen Aplikasi Ruang Guru di Twitter Menggunakan Algoritma Klasifikasi,” *Jurnal Teknoinfo*, vol. 14, no. 2, pp. 115–123, Jul. 2020, doi: 10.33365/JTI.V14I2.679.

[7] D. H. Sunni, I. and Widyantoro, “Analisis Sentimen dan Ekstraksi Topik Penentu Sentimen pada Opini Terhadap Tokoh Publik,” *Jurnal Sarjana Institut Teknologi Bandung Bidang Teknik Elektro dan Informatika*, vol. 1, no. 2, pp. 200–206, 2016.

[8] J. A. Zulqornain, I. Indriati, and P. P. Adikara, “Analisis Sentimen Tanggapan Masyarakat Aplikasi Tiktok Menggunakan Metode Naive Bayes dan Categorial Propotional Difference (CPD),” *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 5, no. 7, pp. 2886–2890, Jun. 2021, Accessed: Feb. 21, 2025. [Online]. Available: https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/9396.

[9] B. Gunawan, H. Sasty, P. #2, E. Esyudha, and P. #3, “Sistem Analisis Sentimen pada Ulasan Produk Menggunakan Metode Naive Bayes,” *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 4, no. 2, pp. 113–118, Dec. 2018, doi: 10.26418/JP.V4I2.27526.

[10] M. F. N. Fathoni, E. Y. Puspaningrum, and A. N. Sihananto, “Perbandingan Performa Labeling Lexicon InSet dan VADER pada Analisa Sentimen Rohingya di Aplikasi X dengan SVM,” *Modem : Jurnal Informatika dan Sains Teknologi.*, vol. 2, no. 3, pp. 62–76, Jul. 2024, doi: 10.62951/MODEM.V2I3.112.

[11] N. Arifin, U. Enri, and N. Sulistiyowati, “Penerapan Algoritma Support Vector Machine (SVM) dengan TF-IDF N-Gram untuk Text Classification,” *STRING (Satuan Tulisan Riset dan Inovasi Teknologi)*, vol. 6, no. 2, pp. 129–136, Dec. 2021, doi: 10.30998/STRING.V6I2.10133.

[12] J. A. Septian, T. M. Fachrudin, and A. Nugroho, “Analisis Sentimen Pengguna Twitter Terhadap Polemik Persepakbolaan Indonesia Menggunakan Pembobotan TF-IDF dan K-Nearest Neighbor,” *INSYST: Journal of Intelligent System and Computation*, vol. 1, no. 1, pp. 43–49, Aug. 2019, doi: 10.52985/INSYST.V1I1.36.

[13] A. C. Khotimah and E. Utami, “Comparison Naïve Bayes Classifier, K-nearest Neighbor and Support Vector Machine in the Classification of Individual on Twitter Account,” *Jurnal Teknik Informatika (Jutif)*, vol. 3, no. 3, pp. 673–680, Jun. 2022, doi: 10.20884/1.JUTIF.2022.3.3.254.

[14] A. Y. Simanjuntak, I. S. S. Simatupang, and A. Anita, “Implementasi Data Mining Menggunakan

Metode Naïve Bayes Classifier Untuk Data Kenaikan Pangkat Dinas Ketenagakerjaan Kota Medan," *Journal Of Science And Social Research*, vol. 5, no. 1, pp. 85–91, Feb. 2022, doi: 10.54314/JSSR.V5I1.804.

[15] A. Nugroho and Y. Religia, "Analisis Optimasi Algoritma Klasifikasi Naive Bayes menggunakan Genetic Algorithm dan Bagging," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 5, no. 3, pp. 504–510, Jun. 2021, doi: 10.29207/RESTI.V5I3.3067.