JURNAL ILMIAH TEKNOLOGI DAN REKAYASA
Vol. 30, No. 02, August 2025, 108 – 118
p-ISSN: 1410-9093, e-ISSN: 2089-8088
https://ejournal.gunadarma.ac.id/index.php/tekno | tekrek@gunadarma.ac.id

Sentiment Analysis of Twitter Data on Indonesia's Cabinet Using Naïve Bayes and Support Vector Machine Algorithms

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Abstract

Twitter has become a widely used platform for information dissemination among internet users and it serves as a valuable data source for sentiment analysis and decision-making. In this context, sentiment analysis is used to automatically categorize user tweets into positive or negative opinions. The Indonesia Maju Cabinet, the current administration under President Joko Widodo has emerging various public opinions regarding their performance and responsibilities. Sentiment analysis provides a method to categorize public opinions on social media. This study uses a dataset collected through a crawling process on Twitter with the keyword "Menteri Jokowi" (Jokowi's Ministers). The obtained data was then analyzed using two algorithms: Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM), to compare their cross-validation results. The analysis results show that the Naïve Bayes Classifier algorithm achieved 91.70% accuracy, 91.69% recall, and 91.69% precision. Meanwhile, the SVM algorithm achieved 96.77% accuracy, 96.71% recall, and 96.71% precision. The difference in accuracy is due to NBC's tendency to misclassify neutral tweets as positive, whereas SVM, despite optimizing class separation, struggled with detecting sarcasm and subtle sentiment shifts, sometimes misclassifying negative tweets as neutral. Based on these results, it can be concluded that both algorithms can be effectively used for classifying opinions about ministers through sentiment analysis, although SVM demonstrates higher accuracy.

Keywords: Naïve Bayes; presidential cabinet; sentiment analysis; SVM; twitter

1. Introduction

Advancements in information and communication technology have significantly impacted the lifestyle changes of the global community. The internet has become a vast source of information, enabling anyone to access knowledge on a variety of topics. These changes necessitate regulations that serve as guidelines with formal legal authority, ensuring fair and secure online interactions. The Indonesian government responded to this need by enacting Law No. 11 of 2008 on Electronic Information and Transactions (ITE Law), which governs various aspects of electronic information [1]. As digital engagement continues to grow, online interactions, particularly on social media platforms, have become an integral part of daily life, influencing communication patterns, business practices, and even governance.

The main goal of the research is to analyze the data from the surveys and to decide whether it is suitable to be analyzed with the use of the discussed data mining methods [2]. The increasing reliance on digital platforms is particularly evident in Indonesia's social media usage. According to a survey by We Are Social, a British media company collaborating with

Article Info: Received February 06, 2025; Accepted July 07, 2025; Published August 23, 2025

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Hootsuite, Indonesians spend an average of 3 hours and 23 minutes daily on social media. A report published on January 30, 2018, titled “Essential Insights Into Internet, Social Media, Mobile, and E-Commerce Use Around The World,” revealed that out of Indonesia's total population of 265.4 million, 130 million are active social media users, with a penetration rate of 49 percent [3].

The Indonesia Maju Cabinet, which is the governing cabinet of Indonesia under President Joko Widodo, consists of four coordinating ministers and 30 sectoral ministers. The cabinet was announced on October 23, 2019, and inaugurated through Presidential Decree No. 113/P of 2019 for the 2019-2024 term. Following the cabinet’s inauguration, newly appointed ministers have become the focus of public opinion and discussion. Before the internet, people expressed their opinions, criticism, and suggestions through print media. However, with the rapid development of technology, many online platforms have emerged as avenues for people to voice their thoughts.

Today, online platforms have become highly popular communication tools among internet users. Twitter, now rebranded as X, remains a major platform for real-time public sentiment [4, 5]. The growth of Twitter usage in recent years has been driven by its faster dissemination of information compared to digital or print news media [6]. Consequently, researchers have developed systems to extract information from Twitter conversations, with one critical piece of information being public sentiment [7, 8]. Sentiment Analysis, a subfield of Natural Language Processing (NLP), is concerned with interpreting individuals' opinions, emotions, and attitudes [9]. Analyzing tweets plays a crucial role in helping businesses develop impactful campaign strategies [10]. Sentiment analysis of Twitter data has become important as it has the potential to influence evaluations of the performance of the Indonesia Maju Cabinet for the 2019-2024 period. The objective of sentiment classification is to automatically group user opinions into positive or negative sentiments [10].

The previous studies have demonstrated the effectiveness of various sentiment analysis techniques in different contexts, including political sentiment, product reviews, and government policies. Notably, several studies have applied sentiment analysis to Twitter data using various algorithms to examine public opinion on a range of topics [11]. For instance, Pebrianto et al. analyzed sentiment toward Indonesian ministers using SVM and K-Nearest Neighbor [12], while Ismail et al. employed Fine-Grained Sentiment Analysis to study reactions to the Indonesian presidential debates [13]. Similarly, Haryanto et al. used SVM with a Polynomial Kernel to analyze product reviews in Indonesian [14], Winarno et al. utilized a Lexicon-Based approach to assess sentiment regarding the Jokowi administration’s social welfare initiatives during the pandemic [15], and Muttaqin et al. compared Naïve Bayes and SVM in analyzing public sentiment on Indonesia's capital relocation [16]. While prior research has explored sentiment analysis in Indonesian politics, there remains a need for a focused comparison of NBC and SVM in assessing public sentiment toward Indonesian ministers specifically.

Therefore, the objective of this study is to compare the performance of NBC and SVM in sentiment analysis of Indonesian political figures, specifically ministers, based on public perceptions of their performance. By leveraging Twitter as a source of real-time public opinion, this research aims to provide both theoretical and practical contributions to the field of sentiment analysis. Additionally, it seeks to evaluate the effectiveness of political leadership in the digital space by analyzing algorithmic performance within the context of Indonesian political sentiment.

To achieve these objectives, this study seeks to answer the following research question: Which classifier, NBC or SVM demonstrates higher accuracy and effectiveness in analyzing public sentiment toward Indonesian ministers based on Twitter data.

2. Research Methods

2.1 Conceptual Framework

This study provides both theoretical and practical insights, particularly for political analysts, policymakers, and researchers interested in real-time public opinion monitoring. Guided by the conceptual framework (Fig. 1), the research systematically evaluates the strengths and weaknesses of each sentiment analysis algorithm. SVM model separates and constructs hyper plane which can be used for classification [17].

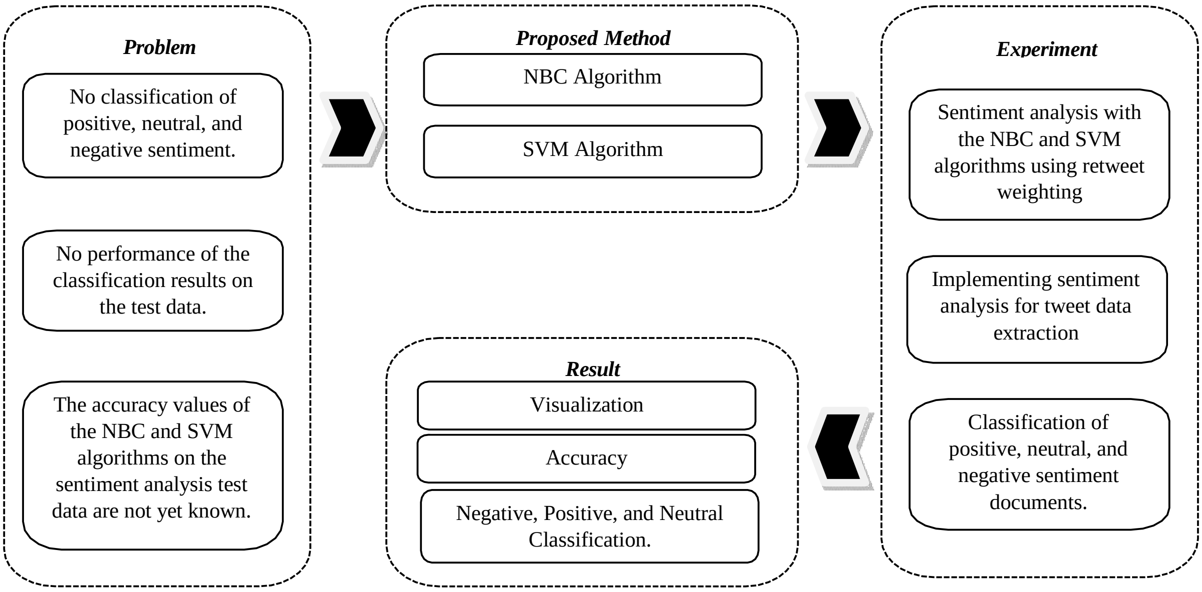


Figure 1. Conceptual Framework

Based on the problems stated, this study focuses on sentiment analysis by addressing the classification of positive, neutral, and negative sentiments and evaluating the performance of algorithms on test data. The proposed method involves using the SVM and NBC algorithms to improve sentiment classification accuracy. Experiments were conducted by applying sentiment analysis using retweet weighting and tweet data extraction to categorize documents based on sentiment. The research results include data visualization, algorithm accuracy measurement, and the distribution of negative, positive, and neutral sentiment classifications derived from the analysis.

2.2 Data Collection

This study collected 29,670 tweets using the Twitter API integrated with R Studio, employing keywords such as "#menterijokowi," "kabinet Indonesia maju," and "menteri jokowi" to capture public sentiment on the Kabinet Indonesia Maju (2019–2024). Data collection was carried out once using the Twitter API. The collected data was then processed and tidied up by performing preprocessing consisting of Cleansing, Case folding, Slang Word, Stemming, Tokenizing, and Stopword removal following previous method [18]. The data required in this study consists of two types, including training data and test data. The training data used was taken from a collection of tweets that had been manually labeled with their sentiment classes and used as training data to determine the sentiment analysis model. This model will then be used to classify tweets in their sentiment classes. The example of the tweets taken are below in Table 1.

Table 1. The Example of Tweets Taken in This Study

Text
RT @Ajek_Channel: Tagar Senin 06.00 WIB #DifitnahTerorisDikurasSDAnya Usai dianggap sukses kelola sea games, Erick Thohir ditunjuk jd Ket...
@edo_macho @Nur_A90 @veragustian _ Mereka yang menjadi menteri antara lain Johnny G. Plate, Syahrul Yasin Limpo, da...https://t.com/HL.Tsnbhh5Z
Bukannya bantu ITDC agar siap penyelenggara moto gp kemenporanya malah kongkalikong sama khofiffah mau nikung te... https://t.co/hfuQacAB0J
RT @SondoroMusic: Sengaja mau hancurkan yang sudah ditata oleh pak @jokowi dan @basuki_btp. Dendam kesumat krn dulu pakde lalu dipe...
RT @satoedoeasatoe: Jauh hari, sejak 2017, sy orang pertama yang sudah bilang bhw susi akan dihempas dr kursi menteri jk jokowi menang kembali.
Jauh hari, sejak 2017, sy orang pertama yang sudah bilang bhw susi akan dihempas dr kursi menteri jk jokowi menang kembal... https://t.co/vqeOiiOFNz
RT @NusantaraTho: YTH: Pak @jokowi Etiskah kebijakan Menteri Keuangan, menaikkan iuran BPJS Rakyat, sementara memberi BONUS buat Direksi...
@Prapat_Nixon Lucu sich...
Kemenkeu melaporkan kepada DPDRI tentang kebijakan @kemendagri. Apa bu SM Menko di a... https://t.co/RHdOoTvgQh
Pertemuan Bilateral Presiden @jokowi dengan Perdana Menteri Australia @ScottMorrisonMP, Bangkok, 4 November 2019. V... https://t.co/W6EToK35AW
Pertemuan antara Presiden @jokowi dan Perdana Menteri Australia @ScottMorrisonMP dihelat di ruang pertemuan yang ad...https://t.co/TXFXbO7iJD

2.3 Preprocessing Steps

The raw data processing stage involves converting text data from Twitter into a data frame for analysis in R Studio. The preprocessing steps include cleansing, case folding, tokenizing, filtering, and stemming [6].

1. Cleansing: Removes URLs, HTML tags, punctuation, hashtags, retweets, extra spaces, mentions, and twitter usernames (@username)
2. Case Folding: Converts uppercase letters to lowercase to standardize text for sentiment analysis (e.g., MARAH becomes marah, KUat becomes kuat)
3. Slang Word Handling: Converts informal words into their standard forms (e.g., jln become jalan, dr become dari).
4. Stemming: Groups words into their root forms (e.g., hibur, hiburan, menghibur become hibur).
5. Tokenization: Splits text into individual words, removing punctuation and non-letter symbols.
6. Stopwords Removal: Eliminates irrelevant words that do not contribute to sentiment analysis (e.g., tetapi, untuk, dengan).

2.4 Weighting

In this step, tweets are assigned weights based on polarity and subjectivity using an Indonesian-specific lexicon-based approach. The sentiment score of each tweet is calculated by subtracting the count of negative words from the count of positive words such as in Table 2.

Table 2. Scoring of Twitter Data

No	Score	Text
1	2	rocky gerung prabowo subianto cahaya perdana
2	2	rocky gerung prabowo subianto cahaya perdana
3	2	rocky gerung prabowo subianto cahaya perdana
4	0	prestasi maksimal kontroversi minimal
5	1	penasaran tunggu umumin siang muncul trending topic twitter
6	0	jasa followers twitter murah hubung
7	0	jasa instagram followers aktif jasa instagram followers aktif Indonesia
8	-2	jasa instagram followers pasif jasa instagram followers pasif
9	0	pppa gusti ayu bintang dharmawati wakil agama zainut tauhid gerak jalan rangka
10	0	pppa gusti ayu bintang dharmawati wakil agama zainut tauhid gerak jalan rangka

The next step after obtaining the sentiment score for each tweet is to convert the score into sentiment categories:

- Positive: If the score is greater than 0 ($x > 0$)
- Neutral: If the score is equal to 0 ($x = 0$)
- Negative: If the score is less than 0 ($x < 0$)

2.5 Machine Learning Model Selection

1. NBC

   Naïve Bayes is based on Bayes' Theorem, which is expressed as Eq.1.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad (1)$$

   where:
   $P(A|B)$: posterior probability.
   $P(B|A)$: likelihood probability.
   $P(A)$: The probability of event A.
   $P(B)$: The probability of event B (evidence).

2. SVM

   In the context of SVM, a hyperplane can be defined as Eq. 2.

$$w \cdot x + b = 0 \quad (2)$$

   where:
   w: is the weight vector.
   x: is the feature vector of the data.
   b: is the bias or offset of the hyperplane.

   The goal of SVM is to find the values of w and b that maximize the margin, which is calculated as Eq. 3.

$$Margin = \frac{2}{\|w\|} \quad (3)$$

   To maximize the margin, SVM minimizes ‖w‖ (the norm of the weight vector) with the constraint that all data points must be correctly classified using Eq. 4.

$$yi(w \cdot xi + b) \geq 1 \quad (4)$$

   where yi is the class label (for example, +1 for the positive class and -1 for the negative class).

3. Results and Discussion

Sentiment analysis is applicable to a wide array of challenges relevant to human-computer interaction, and is also valuable to disciplines such as sociology, marketing and advertising, psychology, economics, and political science [19]. While elections represent critical events in democratic societies, offering citizens the opportunity to express their views and political preferences [20]. The study will employ SVM and NBC for aspect-level sentiment analysis [21], and it's limited to Twitter media social as the data processed with non-formal language needed to paraphrase to get the good result for the modelling of machine learning [22]. The study identifies key patterns in the dataset, such as the dominance of certain keywords like "Prabowo," "Papua," and "Radikal," which indicate public discussions on political and security issues. The sentiment distribution shows that 60% of the tweets are classified as positive, 30% as negative, and 10% as neutral (Fig. 2). A closer examination of keyword sentiment distribution reveals distinct trends. Tweets mentioning "Prabowo" are predominantly classified as positive, reflecting public support and discussions on his leadership and political prospects. In contrast, tweets containing "Papua" display a more polarized sentiment, with a mix of negative and neutral classifications. This suggests that discussions on Papua often revolve around socio-political issues, security concerns, and regional developments, leading to diverse public reactions. The complexity of the Papuan issue, ranging from calls for independence, human rights concerns, to development disparities, appears to contribute to this sentiment fragmentation [23]. Moreover, the prevalence of neutral tones could also indicate uncertainty, lack of information, or cautious engagement by the public when addressing sensitive topics. Meanwhile, the keyword "Radikal" is associated mainly with negative sentiment, highlighting concerns about extremism and radical movements in Indonesia. This consistent negativity suggests a heightened public sensitivity to radical ideologies, possibly influenced by recent national discourse, government counterterrorism measures, or media framing [24]

These findings align with existing studies that suggest political topics tend to evoke stronger opinions, resulting in a higher proportion of both positive and negative sentiments [25]. In contrast, discussions related to security issues often exhibit a skew toward negative sentiment, reflecting public concerns over stability and governance. The influence of these keywords on sentiment classification underscores the role of Twitter as a dynamic platform for public discourse, where political and security-related discussions shape collective sentiment.

Figure 2. Word Cloud Dataset

After content analysis, a weighting test is performed to measure word importance within a document relative to the entire dataset. The results help identify the best features for the classification algorithm. For example, the sentence "RT doorstop Menkominfo rekan-rekan media gelar acara konferensi pers Kemkominfo Indon." was then translated into English into *"RT doorstop Ministry of Communication and Information colleagues media hold press conference Ministry of Communication and Information Indonesia."*.

After tokenization, the translated sentence becomes:

["rt", "doorstop", "Ministry", "of", "Communication", "and", "Information", "colleagues", "media", "hold", "press", "conference", "Indonesia"]

Based on the available lexicon dictionary, polarity and subjectivity values are assigned to each word (Table 3).

Table 3. Lexicon Dictionary Word Table

Word	Polarity	Subjectivity
Rt	0.1	0.2
doorstep	0	0
Ministry	0	0.1
Of	0	0
Communication	0	0.1
And	0	0
Information	0	0.1
colleagues	0.2	0.5
Media	0.1	0.4
Hold	0.1	0.2
Press	0	0.1
conference	0.1	0.2
Indonesia	0	0.1

The overall polarity and subjectivity are calculated. The polarity score is determined as 0.0462, indicating that the sentence is slightly positive but almost neutral. Meanwhile, the subjectivity score is 0.1538, suggesting that the sentence contains some opinion elements but remains fairly objective. This method ensures that no result is strictly zero while maintaining meaningful and contextually relevant values. To access the complete lexicon dictionary, the Pattern library's source code can be found on GitHub at https://github.com/clips/pattern, with the sentiment lexicon available in pattern/text/en/wordlist.py.

Evaluation metrics such as accuracy, precision, recall, and F1-score are essential for assessing the performance of a classification model. Accuracy represents the percentage of correct predictions out of the total predictions made by the model. Precision measures the proportion of correctly predicted positive cases among all predicted positives, indicating how reliable the model is when identifying positive instances. Meanwhile, recall evaluates the model's ability to correctly identify actual positive cases, reflecting its sensitivity to positive instances. A high recall suggests that the model effectively captures most positive examples in the dataset. F1-score, the harmonic mean of precision and recall, provides a balance between the two metrics, making it especially useful in situations involving class imbalances. In this study, the results show that SVM outperforms NBC in terms of accuracy, precision, recall, and F1-score.

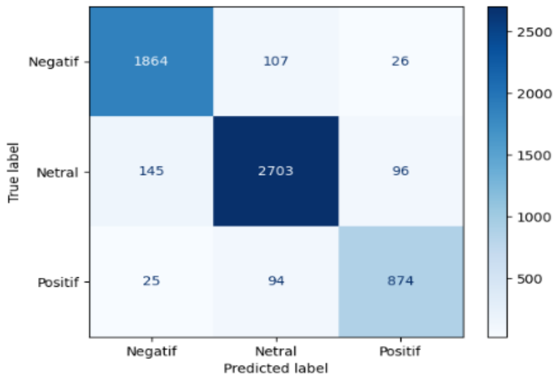
Table 4. Accuracy Value of NBC Model

Class	Precision	Recall	F1-Score	Support
Negative	0.9164	0.9334	0.9248	1997
Neutral	0.9308	0.9181	0.9244	2944
Positive	0.8775	0.8802	0.8788	993
accuracy			0.9169	5934
macro avg	0.9082	0.9106	0.9094	5934
weighted avg	0.9170	0.9169	0.9169	5934

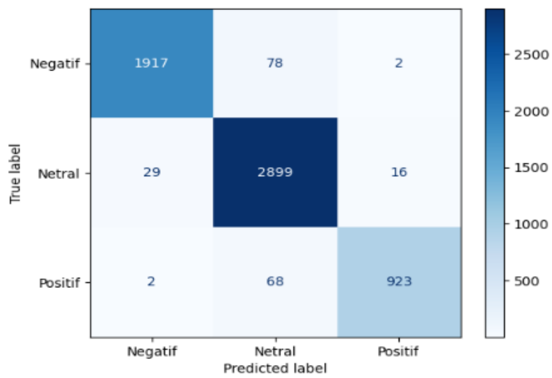
The accuracy, precision, recall, and F1-score of the NBC model are 91.69%, 91.70%, 91.69%, and 91.69%, respectively (Table 4). In comparison, the SVM model achieves higher performance, with an accuracy of 96.71%, precision of 96.77%, recall of 96.71%, and F1-score of 96.71% (Table 5). These results indicate that the SVM model outperforms the NBC model in all evaluation metrics, demonstrating its superior ability to classify data correctly. Higher precision suggests that SVM makes fewer false positive errors, while the improved recall indicates better identification of relevant instances. The increase in F1-score further confirms that SVM maintains a better balance between precision and recall, making it a more reliable choice for this classification task. Furthermore, the SVM confusion matrix indicates an increase in the number of correct predictions, while the number of false positives and false negatives slightly decreases compared to Naive Bayes (Fig. 3).

Table 5. Accuracy Value of SVM Model

Class	Precision	Recall	F1-Score	Support
Negative	0.9841	0.9599	0.9719	1997
Neutral	0.9521	0.9847	0.9681	2944
Positive	0.9809	0.9295	0.9545	993
accuracy			0.9671	5934
macro avg	0.9723	0.9581	0.9648	5934
weighted avg	0.9677	0.9671	0.9671	5934



(a) NBC



(b) SVM

Figure 3. Confusion Matrix Comparison for NBC and SVM Algorithms

The analysis results indicate that the SVM algorithm outperforms the NBC algorithm in terms of accuracy and class separation. Several key performance metrics highlight the advantages of SVM over NBC. SVM achieved a precision of 96.71%, while NBC obtained 91.69%, demonstrating that SVM is more effective in correctly predicting the target class.

The accuracy of SVM reached 96.77%, whereas NBC obtained 91.70%, indicating that SVM identifies tweets more accurately, with fewer false positives and false negatives than NBC, as also mentioned in a previous study [26]. SVM's recall rate of 96.71% and F1 score of 96.71% further emphasize its ability to maintain a strong balance between precision and recall, making it a more reliable classifier for this dataset.

A closer inspection of misclassified tweets provides insights into why SVM outperformed NBC. NBC exhibited a tendency to misclassify neutral tweets as positive, likely due to its reliance on word probabilities without considering contextual meaning. In contrast, SVM, which optimizes class separation, struggled with detecting sarcasm and subtle sentiment shifts, sometimes misclassifying negative tweets as neutral. Additionally, NBC was more prone to false positives when handling tweets with ambiguous language or mixed sentiment, whereas SVM was more effective in differentiating overlapping sentiment classes.

The structure of the dataset itself played a key role in SVM's superior performance. Political discourse on Twitter often contains nuanced language, conflicting sentiments, and indirect expressions, which require a classifier capable of identifying complex relationships between words. SVM's ability to construct a non-linear decision boundary enabled it to better capture these variations, while NBC's assumption of feature independence limited its ability to do so. Additionally, the dataset contained a mix of formal and informal language, as well as slang and abbreviations, which SVM handled more effectively by leveraging a more flexible classification approach. Overall, SVM's strength lies in its ability to generalize well across diverse linguistic patterns and manage class imbalances, making it a more effective choice for sentiment classification in this study. Future work could further refine classification accuracy by incorporating hybrid models or deep learning techniques to improve sentiment detection in challenging textual contexts.

However, there are several limitations to this study. Firstly, the dataset is restricted to tweets, which may not represent the diversity of public sentiment across different platforms or demographics. Additionally, the reliance on basic machine learning models like NBC and SVM might not capture the complexity of sentiment expressed in social media posts as effectively as more advanced techniques. Further improvements can be made by incorporating more advanced models, such as deep learning techniques like Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT), which have shown to provide higher accuracy in understanding context and nuances in language. Expanding the scope of the analysis to include other forms of media and using more sophisticated models could enhance the robustness and accuracy of sentiment analysis in political contexts.

4. Conclusions

This study concludes that SVM outperforms NBC in sentiment analysis, particularly when handling complex and non-linear textual data. The preprocessing steps, including filtering, case folding, and stemming, are crucial for enhancing model accuracy. While SVM demonstrates superior performance, this study is limited by its focus on Twitter data, which may not fully represent public sentiment across different platforms. Additionally, traditional machine learning models like NBC and SVM may struggle with context-dependent sentiment, sarcasm, and linguistic variations. Future research should explore deep learning techniques such as Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT), which have shown greater accuracy in capturing sentiment nuances.

Expanding the dataset scope and incorporating more sophisticated NLP techniques could further improve sentiment analysis in social media and political discourse. This study provides valuable insights into the application of NLP techniques for analyzing public sentiment on social media, offering practical implications for policymakers, researchers, and political analysts.

Acknowledgment

The authors would like to acknowledge Fitri Kurniasari, Ph.D for technical support.

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