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# Sentiment Analysis of the 2024 Indonesian Presidential Dispute Trial Election using SVM and Naïve Bayes on Platform X

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**Abstract**−Indonesian presidential dispute trial election are crucial activities in the democratic process where open exchanges of views and opinions occur. Sentiment analysis can help understand public opinion regarding these sessions. This study aims to conduct sentiment analysis of the 2024 Indonesian presidential dispute trial election using the Support Vector Machine (SVM) and Gausian Naïve Bayes (GNB) with Nazief Adriani and Sastrawi stemming methods on Platform X. The research addresses the challenge of uncertainty in interpreting public sentiment towards Indonesian presidential dispute trial election. SVM and GNB was chosen for its ability to classify large and complex data sets. The Nazief Andriani and Sastrawi stemming techniques were employed to reduce words to their base forms, thereby enhancing the quality of text analysis. The study was conducted on Platform X, which provides access to text data from various sources including social media and news platforms. The data used covered specific periods before, during, and after Indonesian presidential dispute trial election. The keywords used for the crawling process are "*sidang sengketa pilpress*", "*sidang sengketa pemilu*", and "*sidang pilpres*". The classification technique is carried out by classifying it into two classes, namely positive and negative. In applying sentiment analysis using machine learning methods, there are several methods that are often used. Based on the results comparation of tests carried out on 2,443 tweets using SVM with Sastrawi stemming method produce the best accuracy of 91.1%, precision 90%, recall 91%., and F1-Score 91%.

**Keywords**: Sentiment Analysis; Sastrawi; Support Vector Machine (SVM); Indonesian Presidential Election.

## 1. INTRODUCTION

Indonesia is a unitary state in the form of a republic. The government system applied is the presidential system, in which the president serves as both the head of state and head of government. The presidential and vice-presidential elections are conducted through general elections, with a five-year term and the possibility of being re-elected for one additional term [1]. The general election process guarantees the legitimacy of the president and vice president as leaders elected by the people.

Violations of the election can occur at every stage of the process, including planning, preparation, and vote counting [2]. First, there are still many disputes and violations committed by various parties during the election in our country. Second, various parties involved in the election must be aware of the changes in dispute resolution caused by the enactment of the new Election Law. Third, a number of court decisions and procedures related to the election have marred the dispute resolution process, thus requiring a review. These judicial inconsistencies and procedural inefficiencies have undermined public trust in the electoral process, making it imperative to re-evaluate and refine these mechanisms to restore integrity and transparency [3]. The establishment of a process to challenge the election results is one of the new aspects in the last two elections in Indonesia.

Sentiments in elections refer to the views, feelings, and opinions considered by voters regarding candidates, political parties, political issues, and the election process itself. Social media and online news play an important role in shaping voter sentiment [4]. By understanding sentiment in elections, candidates and political parties can design more effective campaign strategies and better understand the needs and desires of voters. In addition, relevant government and institutions can also use sentiment analysis to improve the integrity and transparency of the election process, as well as to ensure a more accurate representation of the people's voice. Moreover, tracking voter sentiment over time can help identify emerging trends and issues, allowing for more responsive and adaptive governance [5]. Analyzing sentiment can also provide insights into the impact of political advertisements, speeches, and debates, thereby enabling more targeted and impactful communication efforts [6].

Sentiment analysis plays a crucial role in measuring the general mood and public opinion towards candidates, parties, and policies [7]. Sentiment analysis in elections covers the views, feelings, and opinions of voters [8]. This approach can provide deep insights into voter preferences and concerns, which are crucial for campaign strategy formulation. Understanding the sentiments of different voter groups enables the creation of more personalized and engaging interactions with voters [9]. This has the potential to increase voter mobilization and support.

Sentiment analysis plays a crucial role in guiding individuals in their decision-making process when selecting a presidential candidate, assisting in assessing a candidate's suitability for national leadership. Previous studies on sentiment analysis employing classification algorithms like Naïve Bayes and SVM have demonstrated different levels of accuracy. For instance, Gerry Nugroho's analysis of the 2020 American Presidential Election showed that SVM achieved higher accuracy at 82%, compared to Naïve Bayes at 69% [10]. This suggests that SVM may be more effective in handling complex and high-dimensional data typically found in election-related sentiments. Similarly, a study by Damayanti and Lhaksmana utilized the Support Vector Machine (SVM) algorithm with Word2Vec feature extraction to classify sentiment in public opinion texts about presidential candidates for the 2024 election, using data

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sourced from Twitter. Their study achieved optimal performance with an 80:20 train-test split, resulting in a precision score of 88.94%, recall of 93.08%, F1-score of 90.43%, and accuracy of 90.75% [11]. Additionally, Damayanti and Lavanya tested three machine learning algorithms—Naïve Bayes, SVM, and Decision Trees—on an online product review dataset. Their results indicated that SVM had the highest accuracy at 85%, effectively handling high-dimensional data and complex linguistic structures [12]. Mustikasari et al. compared different stemming methods and found that the Sastrawi algorithm was effective, returning 95.2% of tested affix words to their root forms, while the Nazief & Adriani algorithm achieved 92.4% and the Arifin Setiono algorithm reached 89% [13]. Research conducted by Vincentius Prasetyo using the Nazief Adriani stemming method to analyze customer review sentiment at a coffee cafe was able to produce the highest accuracy of 93.3%[14]. This indicates that stemming methods can significantly impact the accuracy of sentiment analysis models. In this research, the stemming optimization process is also carried out using text-preprocessing techniques. This is based on research conducted by M. Ulil Albab resulting in the conclusion that before stemming with text processing techniques produced an accuracy of 95.86%, after stemming stemming with text text processing produced an accuracy of 99.93%[15]. In addition, the stemming process is also carried out with the TF-IDF weighting method in this research, based on research conducted by Septian Firman S, the experimental results show that the data through the stemming process with TF-IDF weighting gets the best accuracy results with a value of 86.84% compared to the data through the stemming process with TF weighting getting an accuracy value of only 77.82%[16].

Based on related research, this study will conduct a model comparison of SVM and GNB in Sentiment Analysis of the 2024 Indonesian Presidential Dispute Trial Election on Platform X to determine the performance comparison of the two models in terms of accuracy, precision, recall and F1-Score. GNB and SVM are used as the main reference in model comparison in this study because Support Vector Machine (SVM) and Gaussian Naïve Bayes (GNB) methods showed optimal results in previous studies and both algorithms are capable of text data whose number of classifications is more than two classes, namely positive, negative, and neutral. This study applies two stemming methods, namely Sastrawi and Nazief Adriani to determine the effect of stemming on the accuracy of SVM and GNB models. Based on research conducted by Mustikasari, stemming using the sastrawi method produces the best accuracy of 95.2%, compared to stemming using the Nazief Adriani method which produces an accuracy of 92.4 and stemming using the arifin sentiono method produces an accuracy of 89%[13]. Research conducted by Vincentius Prasetyo showed the opposite results, where the results showed that stemming with the Nazief Adriani method produced the best results, with an accuracy of 93.3%[14]. Therefore, this research conducts a comparison using the above modes of algorithms and stemming methods to identify the most effective combination of stemming methods and classification algorithms for sentiment analysis in the context of the Indonesian Presidential Dispute Trial Election and find out whether using the same technique in different cases can produce the same level of accuracy as previous research.

## 2. RESEARCH METHODOLOGY

This research adopts a quantitative approach, utilizing the Support Vector Machine (SVM) and Gaussian Naive Bayes (GNB) algorithms integrated with the stemming techniques of Sasstrawi and Nazief/Adriani. The choice of these machine learning algorithms and stemming methods is based on their effectiveness in handling large and complex datasets, as well as their proven capability in sentiment analysis tasks[11], [13]. By combining these machine learning algorithms with the stemming techniques, the research aims to achieve accurate and reliable sentiment analysis results, particularly in the context of the 2024 Indonesian presidential dispute trial election. The integration of SVM and GNB with Sasstrawi and Nazief/Adriani stemming methods enhances the capability of the sentiment analysis model to effectively classify and analyze sentiments expressed in the textual data obtained from various sources.

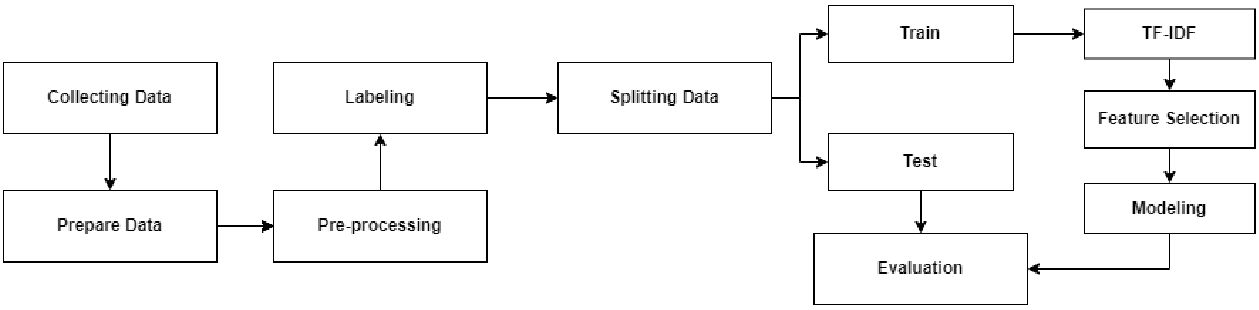


**Figure 1.** Flow Diagram Research Methodology

In this research, can be seen in Figure 1, conducted in multiple stages, data was collected from Platform X using the Tweet Harvest v2.6.8 tool, focusing on tweets related to the 2024 Indonesian presidential runoff election. The dataset underwent rigorous cleaning to eliminate irrelevant information. Pre-processing included case folding, text normalization, stop words removal, and stemming using the Sastrawi and Nazief Adriani algorithms. Next, the cleaned data was labeled for sentiment and split into training and testing subsets. To assess word importance, TF-IDF

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weighting was applied, followed by feature selection to enhance model efficiency. Sentiment classification models were constructed using Support Vector Machine (SVM) and Gaussian Naïve Bayes (GNB). Evaluation of these models focused on metrics such as accuracy, precision, recall, and F1-score.

### 2.1 Collecting Data

Data for this study was collected from Platform X, which provides access to text data from various sources, including social media and news platforms. The data covered specific periods before, during, and after the Indonesian presidential dispute trial election. Data collection was performed using the crawling technique with the assistance of the Tweet Harvest v2.6.8 tool developed by Helmi Satria. Twitter data crawling involves the downloading of data using the Twitter API [13]. This process of crawling entails the use of specific keywords related to the 2024 Indonesian presidential dispute trial election to retrieve relevant tweets.

### 2.2 Prepare Data

After the data collection phase, the collected dataset underwent several preparation steps to ensure its appropriateness for sentiment analysis. Cleanning Data, the dataset was subjected to a rigorous cleaning process to eliminate irrelevant or redundant data. This involved the removal of retweets, duplicate posts, and non-textual content, such as images or links, that might not contribute to the sentiment analysis process. By filtering out such noise, the dataset was refined to contain only relevant textual content necessary for sentiment analysis. Following the cleaning and filtering phase, the text data was tokenized. Tokenization involves breaking down the textual data into individual tokens, which could be words, phrases, or symbols [17].

### 2.3 Pre-processing Data

The pre-processing phaes, conducted in multiple stages aimed to standardize and enhance the quality of the text data for sentiment analysis, the process stage can be seen in Figure 2

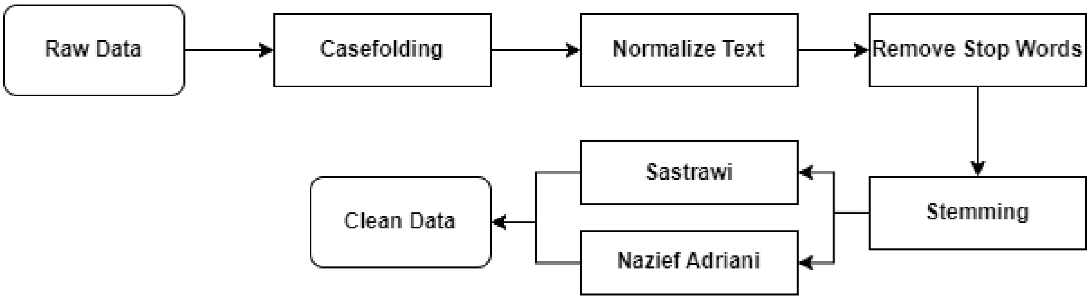


**Figure 2.** Flow Diagram Pre-processing Data

a. Raw Data

The raw data for this study was sourced from Platform X, this unprocessed data initially contained a mix of relevant and irrelevant information, including duplicate posts, retweets, and non-textual content like images or links. Therefore, the raw data required extensive cleaning and preprocessing to ensure its suitability for sentiment analysis.

b. Casefolding

All text data underwent case folding, where the entire corpus was converted to lowercase. This process ensured uniformity in text representation, eliminating any discrepancies that may arise from variations in letter case [18].

c. Normalize Text

Special characters, punctuation marks, and other non-alphanumeric symbols were addressed in this step [19]. These elements were either removed entirely or replaced with standardized representations to simplify the text and ensure consistency across the dataset. For instance, apostrophes, hyphens, and other similar characters were normalized to their base forms.

d. Remove StopWords

Commonly occurring but irrelevant words, known as stop words, were removed from the text data [20]. These words, such as articles, prepositions, and conjunctions, do not carry significant semantic meaning and are unlikely to contribute meaningfully to sentiment analysis. By eliminating stop words, the dataset was streamlined, focusing only on the words that carry more substantial sentiment-related information. The removal of stop words is a crucial preprocessing step in text analysis because it reduces the noise in the data, allowing the algorithms to concentrate on the more informative parts of the text [21]. This step helps in enhancing the clarity and relevance of the data, making it easier to identify patterns and trends related to sentiment. Without the clutter of stop words, the remaining words are those that more directly express opinions, emotions, and sentiments, such as adjectives, nouns, and verbs that indicate positive or negative sentiments.

e. Stemming

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The Stemming process is employed to convert words into their base or infinitive verb forms. For instance, the words "berlari," "berlari-lari," and "lari" can be transformed into "lari." This helps reduce the variation of words with similar meanings. Stemming itself actually falls under the data preprocessing process; however, in this study, experiments were conducted using multiple stemming algorithm techniques. Stemming itself is a fundamental part of the data preprocessing process in text mining and natural language processing. It prepares the text for further analysis by removing morphological affixes, which can include prefixes, suffixes, infixes, and circumfixes in languages like Indonesian. However, in this study, experiments were conducted using multiple stemming algorithm techniques to evaluate their effectiveness and efficiency in different contexts. These algorithms might include traditional rule-based approaches, machine learning-based techniques, or hybrid methods that combine multiple strategies to achieve optimal results [22].

1. Sastrawi
   Sastrawi serves as a dictionary or library utilized for word stemming in the Indonesian language. This tool can convert words with affixes in Indonesian into their base forms. The operational procedure of this algorithm starts with the Sastrawi algorithm conducting data preprocessing, which involves converting all letters to lowercase, eliminating URLs, and removing irrelevant characters. Following the completion of the preprocessing phase, the Sastrawi algorithm proceeds to perform stemming on the words within the text by identifying and removing prefixes, suffixes, and affixes. Subsequently, once all relevant prefixes, suffixes, and affixes are eliminated, the word is returned to its base or root form. This base form can then be used for various natural language processing tasks, such as text analysis, sentiment analysis, and information retrieval, making Sastrawi an invaluable tool for researchers and developers working with Indonesian text data. Additionally, Sastrawi's comprehensive approach to stemming helps improve the accuracy and efficiency of these tasks by ensuring that words are consistently reduced to their most meaningful forms [23].
2. Nazief Adriani
   The second algorithm, known as Nazief and Adriani (NA), is one of the Indonesian language stemming methods utilized in Natural Language Processing to transform words into their base or root forms. This algorithm is specifically designed to handle the unique morphological structure of the Indonesian language, making it particularly effective for tasks that require accurate identification of word roots. The Nazief and Adriani algorithm employs a comprehensive set of linguistic rules to strip away affixes, including prefixes, suffixes, infixes, and circumfixes, ensuring that the resultant base forms are correct and meaningful [24]. The operational process of this algorithm involves several steps. Initially, the algorithm attempts to identify whether the word has a prefix such as "me-", "di-", "ke-", "se-", or "te-". If so, the prefix will be removed. For example, "makan" will become "akan", and "melakukan" will become "lakukan". Next, the algorithm checks whether the word has a suffix such as "-kan", "-i", "-mu", or "-kah". If present, the suffix will be removed. For instance, "melakukan" becomes "melaku", and "makanan" becomes "makan". If the word contains affixes such as "-nya" and "-ku", these affixes will be removed. For example, "kucingnya" becomes "kucing" and "permainanku" becomes "permainan". This checking process is performed sequentially, with the algorithm examining each possible cutting rule for the word. As a result, the final outcome of this process is that the words return to their base forms.

### 2.4 Labeling

Labeling involves assigning labels or classifications to gathered data. At this stage, data is labeled to ascertain whether each sentence in the dataset expresses a positive, negative, or neutral sentiment. Each sentence is labeled during this process according to its conveyed meaning, aiding in data analysis and decision-making. The labeling technique utilized in this study utilizes the Inset Lexicon dictionary, which follows a lexicon-based approach by assessing and weighting various words based on polarity scores to evaluate public reactions to a specific topic.

### 2.5 Splitting Data

The labeled dataset, comprising tweets related to the 2024 Indonesian presidential dispute trial election, was divided into two subsets:

a. Train

This subset are utilized to train the machine learning models, specifically Support Vector Machine (SVM) and Gaussian Naive Bayes (GNB), on sentiment analysis. Through this process, the models learned to recognize and analyze patterns and features associated with sentiment classification. The training set provided the foundational data necessary for the models to accurately classify sentiments into positive or negative categories.

b. Test

This subset was set aside to evaluate the performance of the trained models on unseen data. By using the test set, I assessed how well the trained SVM and GNB models could generalize and accurately predict sentiments in real-world scenarios. This evaluation was essential for determining the effectiveness and reliability of the sentiment analysis models developed for the 2024 Indonesian presidential dispute trial election on Platform X.

### 2.6 TF-IDF

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TF-IDF, which stands for Term Frequency-Inverse Document Frequency, was utilized to process the pre-processed text data. This method calculates the importance of each word in the dataset by considering its frequency of occurrence in a specific document and across the entire dataset. By applying TF-IDF, words that are more frequent in a particular document but less common across the dataset are assigned higher weights, thus emphasizing their significance in sentiment analysis. This weighted approach allows the algorithm to focus on words that provide the most insight into the content and sentiment of each document, filtering out commonly used words that may not contribute much to the analysis, such as stop words or other high-frequency but low-importance terms [25]. Consequently, TF-IDF enhances the accuracy and relevance of the text data analysis, making it particularly useful for extracting meaningful patterns and trends from large volumes of textual information.

### 2.6 Feature Selection

Feature selection techniques were employed to identify and select the most pertinent and discriminative features for sentiment analysis. This process enhances the efficiency and effectiveness of the sentiment classification models by focusing on the most relevant aspects of the data. Through feature selection, irrelevant or redundant features are eliminated, allowing the models to better capture the essential patterns and characteristics associated with sentiment classification. The benefits of feature selection extend beyond model performance. By reducing the number of features, the computational load is decreased, leading to faster model training and prediction times. This efficiency is particularly important when dealing with large datasets or real-time applications where speed is crucial [26]. A more streamlined feature set can make the model more interpretable, allowing analysts and stakeholders to understand which features are driving the predictions and to gain deeper insights into the factors influencing sentiment.

### 2.6 Modeling

The Support Vector Machine (SVM) and Gaussian Naïve Bayes (GNB) machine learning algorithms were chosen to construct sentiment classification models. SVM and GNB were selected due to their ability to handle large and intricate datasets effectively. Moreover, they have demonstrated remarkable efficacy in sentiment analysis tasks. By utilizing these algorithms, the study aimed to develop robust models capable of accurately classifying sentiments related to the 2024 Indonesian presidential dispute trial election on Platform X.

### 2.6 Evaluation

In this stage, the classification model evaluation was conducted by splitting the data into 20% for testing and 80% for training. The performance of the sentiment classification models was assessed using various evaluation metrics, including accuracy, precision, recall, and F1-score.

a. Precision

Precision assesses the accuracy of the model's positive predictions by calculating the proportion of true positives among all predicted positives.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

TP (true positives) represents the correctly predicted positive instances, and FPFPFP (false positives) denotes the incorrectly predicted positive instances.

b. Recall

Recall, also referred to as sensitivity or the true positive rate, evaluates the model's effectiveness in identifying all actual positive cases

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

FN (false negatives) signifies the actual positive instances that were incorrectly classified as negative.

c. F1-Score

The F1 score is the harmonic mean of precision and recall, offering a single measure that balances both metrics.

$$F1 = \frac{2+Recall+Precision}{Recall+Precision} \tag{3}$$

This score provides a comprehensive assessment of the model's performance, particularly in scenarios with imbalanced class distributions. The F1 score ranges from 0 to 1, with 1 representing perfect precision and recall, and 0 indicating the lowest possible performance.

This evaluation was performed on the test set to ascertain the models' ability to accurately classify sentiments. By analyzing these metrics, the study thoroughly assessed the effectiveness and reliability of the SVM and GNB models in sentiment analysis for the 2024 Indonesian presidential election trial on Platform X.

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## 3. RESULT AND DISCUSSION

In this study, the results are obtained in the form of processes and evaluations. With several stages of processing and evaluation presented through a confusion matrix, we report the results of our analysis.

### 3.1 Data Collection

The data collection process involved using web scraping techniques to gather tweet data from the X platform (formerly known as Twitter) over a two-day period from May 28 to May 30, 2024. A total of 2443 raw tweets were collected during this period. These tweets include various symbols, user handles, URLs, and hashtags, which need to be processed further to extract meaningful information for sentiment analysis. The example of Raw Data Tweet can be seen in Table 1 below.

**Table 1.** Raw Data Tweet

| Index | Raw Data |
|---|---|
| 1 | @tempodotco Amati dan fahami. Betul yah Indonesia hanya pura pemilu? Pilkada Pilbup Pilgub/Pilpres. Krn pemenang sdh di pesan oligarki kapitalis lewat oknum aparat hianat lembaga survei quick count tayang di TV di MKpun sidang gugatan pura pura juga? @KPU_ID @officialMKRI @bawaslu_RI https://t.co/HJQYiegegE |
| 2 | Mari kita jaga kondusivitas pasca putusan sidang MK dengan tidak mudah terprovokasi pemberitaan negatif. Sehingga tahapan Pemilu 2024 dapat berlangsung dengan lancar dan kondusif. Hormati proses demokrasi dengan aman dan damai. #Pemilu2024AmanDamai #SukseskanPemilu2024 https://t.co/4KAwo0qoHw |
| 3 | @165Hati @Nikul_ae @ganjarpranowo @mohmahfudmd Pemilu telah selesai dan telah diputuskan sidang MK bahwa Presiden dan Wakil Presiden terpilih terbukti tidak melakukan kecurangan dan dipilih rakyat secara SAH. |

These raw data tweets contain symbols like '@', '/', and URLs which make them challenging to analyze in their initial form. Thus, we move on to the pre-processing stage to clean and standardize this data.

### 3.2 Pre-processing Data

The pre-processing of data transforms raw data into a clean format suitable for analysis. This process involves three main steps: case folding, normalizing text, and removing stopwords. Case folding converts all text to lowercase to ensure uniformity, thereby eliminating distinctions between uppercase and lowercase letters. For instance, 'TV' is converted to 'tv' and ‘MK’ into ‘mk’. Normalizing text involves converting slang and shorthand into their proper forms, which standardizes the text. For example, 'krn' (short for 'karena') is converted to its full form 'karena'. Finally, removing stopwords involves filtering out common words that do not contribute to sentiment analysis, such as 'dan', and 'di'

**Table 2.** Pre-processing Data

| Step | Raw Data | Result |
|---|---|---|
| Case Folding | @tempodotco Amati dan fahami. Betul yah Indonesia hanya pura pemilu? Pilkada Pilbup Pilgub/Pilpres. Krn pemenang sdh di pesan oligarki kapitalis lewat oknum aparat hianat lembaga survei quick count tayang di TV di MKpun sidang gugatan pura pura juga? @KPU_ID @officialMKRI @bawaslu_RI https://t.co/HJQYiegegE | tempodotco amati dan fahami betul yah indonesia hanya pura pemilu pilkada pilbup pilgub pilpres krn pemenang sdh di pesan oligarki kapitalis lewat oknum aparat hianat lembaga survei quick count tayang di tv di mkpun sidang gugatan pura pura juga kpu_id officialmkri bawaslu_ri t co hjqyiegege |
| Normalize Text | tempodotco amati dan fahami betul yah indonesia hanya pura pemilu pilkada pilbup pilgub pilpres krn pemenang sdh di pesan oligarki kapitalis lewat oknum aparat hianat lembaga survei quick count tayang di tv di mkpun sidang gugatan pura pura juga kpu_id officialmkri bawaslu_ri t co hjqyiegege | tempodotco amati dan fahami betul yah indonesia hanya pura pemilu pilkada pilbup pemilihan gubernur pilpres karena pemenang sudah di pesan oligarki kapitalis lewat oknum aparat hianat lembaga survei quick count tayang di televisi di mkpun sidang gugatan pura pura juga kpu_id officialmkri bawaslu_ri t cowok hjqyiegege |

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| | | |
|---|---|---|
| Remove Stopwords | tempodotco amati dan fahami betul yah indonesia hanya pura pemilu pilkada pilbup pemilihan gubernur pilpres karena pemenang sudah di pesan oligarki kapitalis lewat oknum aparat hianat lembaga survei quick count tayang di televisi di mkpun sidang gugatan pura pura juga kpu_id officialmkri bawaslu_ri t cowok hjqyiegege | tempodotco amati fahami yah indonesia pura pemilu pilkada pilbup pemilihan gubernur pilpres pemenang pesan oligarki kapitalis oknum aparat hianat lembaga survei quick count tayang televisi mkpun sidang gugatan pura pura kpu_id officialmkri bawaslu_ri t cowok hjqyiegege |

In this Table 2, we see the transformation from raw tweets to clean text. The case folding step converts all characters to lowercase, the normalization step changes abbreviations to their full forms, and stopwords removal simplifies the text by filtering out non-essential words. From the initial 2443 raw data entries, the pre-processing steps resulted in 1998 clean data entries ready for further processing.

### 3.3 Stemming

Stemming is the process of reducing words to their root form, which makes analysis more straightforward by consolidating different forms of a word into a single entity. We applied two stemming methods: Sastrawi and Nazief Adriani, to determine which method performs better for our dataset.

**Table 3.** Stemming

| Clean Text | Stemming Sastrawi | Stemming Nazief Adriani |
|---|---|---|
| tempodotco amati fahami yah indonesia pura pemilu pilkada pilbup pemilihan gubernur pilpres pemenang pesan oligarki kapitalis oknum aparat hianat lembaga survei quick count tayang televisi mkpun sidang gugatan pura pura kpu_id officialmkri bawaslu_ri t cowok hjqyiegege | tempodotco amat fahami yah indonesia pura milu pilkada pilbup pilih gubernur pilpres menang pesan oligarki kapitalis oknum aparat hianat lembaga survei quick count tayang televisi mkpun sidang gugat pura pura kpu id officialmkri bawaslu ri t cowok hjqyiegege | tempodotco amat fahami yah indonesia pura pilu pilkada pilbup pemilihan gubernur pilpres pemenang pes oligarki kapitalis oknum aparat hianat lembaga survei quick count tayang televisi mkpun sidang gugat pura pura kpu_id officialmkri bawaslu_ri t cowok hjqyiegege |

In this Table 3, we see the clean text after pre-processing and how it is further transformed by the Sastrawi and Nazief Adriani stemming methods. The Sastrawi method reduces words like "pemilihan" to "pilih", while the Nazief Adriani method sometimes produces slightly different root forms, such as "pesan" becoming "pes". The Sastrawi method tends to preserve more contextually meaningful base forms, which is crucial for accurate sentiment analysis.

### 3.4 Labeling

Labeling involves categorizing clean data into negative, neutral, and positive sentiments based on the Lexicon Inset dictionary. This step is essential for training and evaluating sentiment analysis models.

#### 3.4.1 Sentiment Sastrawi

In the Table 4 the results of applying the Sastrawi stemming method to clean text data related to the 2024 Indonesian presidential election. Each tweet is categorized into negative, neutral, or positive sentiment based on its content after stemming.

**Table 4.** Stemming Sastrawi

| Clean Text Sastrawi | Sentiment Sastrawi |
|---|---|
| tempodotco amat fahami yah indonesia pura pemilu pilkada pilbup pilih gubernur pilpres menang pesan oligarki kapitalis oknum aparat hianat lembaga survei quick count tayang televisi mkpun sidang gugat pura pura kpu id officialmkri bawaslu ri t cowok hjqyiegege | Negatif |
| mari jaga kondusivitas pasca putus sidang mk mudah provokasi berita negatif tahap pemilu lancar kondusif hormat proses demokrasi aman damai pemilu amandamai sukseskanpepemilu t cowok kawo qohw | Positif |
| hati nikul ae ganjarpranowo mohmahfudmd pemilu selesai putus sidang mk presiden wakil presiden pilih bukti curang pilih rakyat sah | Netral |

#### 3.4.2 Sentiment Nazief Adriani

In the Table 5 presents the outcomes of applying the Nazief Adriani stemming method to the same dataset. Similar to the Sastrawi method, tweets are classified into negative, neutral, or positive sentiment categories based on their processed text.

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**Table 5.** Stemming Nazief Adriani

| Clean Text Nazief Adriani | Sentiment Nazief Adriani |
|---|---|
| tempodotco amat fahami yah indonesia pura pemilu pilkada pilbup pemilihan gubernur pilpres pemenang pes oligarki kapitalis oknum aparat hianat lembaga survei quick count tayang televisi mkpun sidang gugat pura pura kpu_id officialmkri bawaslu_ri t cowok hjqyiegege | Negatif |
| mar jaga kondusivitas pasca putus sidang mk mudah provokasi pemberitaan negatif tahap pemilu lancar kondusif hormat proses demokrasi aman damai pemilu amandamai sukseskanpemilu t cowok kawo qohw | Positif |
| hati nikul_ae ganjarpranowo mohmahfudmd pemilu selesa diputuskan sidang mk presiden wakil presiden pilih bukti kecurangan pilih rakyat sah | Negatif |

Based on Table 4 and 5, can be seen how different stemming algorithms can influence the categorization of sentiment in textual data related to the Indonesian presidential election, highlighting their role in preprocessing for sentiment analysis. Each tweet is assigned a sentiment label based on its content after stemming. The labels indicate whether the sentiment expressed in the tweet is negative, neutral, or positive. For instance, tweets discussing controversial topics or using negative language are labeled as "Negatif," whereas tweets promoting peaceful and democratic processes are labeled as "Positif." Based on the labeling process on clean data using the literary method, 968 negative, 510 neutral, and 518 positive are generated. While labeling on clean data using the Nazief Adriani method resulted in 813 negative, 547 neutral, and 636 positive.

### 3.5 Feature Extraction and Feature Selection

The feature extraction and feature selection process was conducted to identify the optimal features using the TF-IDF method for feature extraction, followed by the Chi-Square method for feature selection. This process resulted in the identification of 500 top features from 13,944 clean data features using Sastrawi stemming and 500 top features from 14,535 clean data features using Nazief Adriani stemming.

### 3.6 Evaluation

The evaluation phase is essential in the analysis process as it measures the performance of the sentiment classification models. Following feature extraction and selection, the models were trained and assessed to determine their accuracy in sentiment classification. This evaluation included multiple steps, such as splitting the dataset into training and testing sets, applying machine learning models, and calculating performance metrics.

#### 3.6.1 Sentiment Evaluation

Based on the sentiment of the Indonesian people towards the 2024 presidential election dispute hearing on platform X. Word clouds visually represent the most frequently occurring words in the dataset. Larger and thicker words indicate higher frequency. Separate word clouds for negative and positive sentiments help us understand the dominant themes in the public discourse.

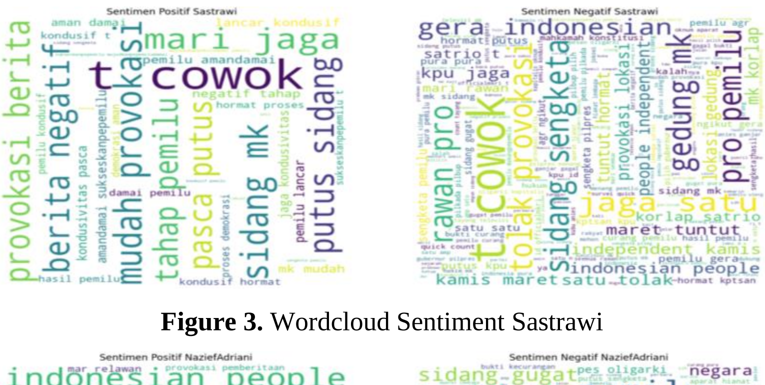


**Figure 3.** Wordcloud Sentiment Sastrawi

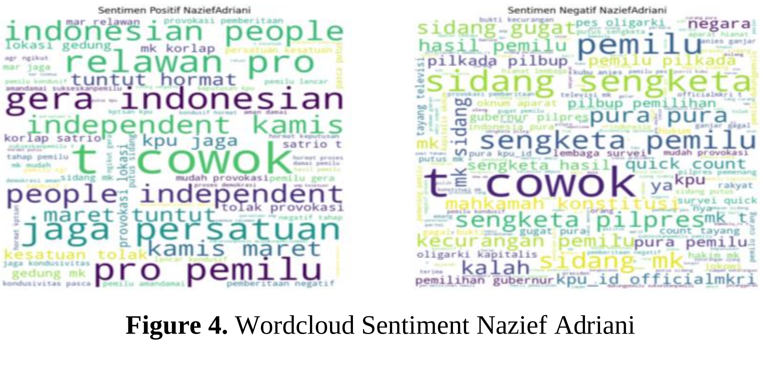


**Figure 4.** Wordcloud Sentiment Nazief Adriani

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In figures 3 and 4, these visualizations help in quickly grasping the general mood and major themes in the public discourse regarding the election dispute. It can be seen that the frequency of the most frequently occurring words for both negative and positive sentiments can be seen by the thickness of the color and the size of the word. The thicker and larger the color, the more often the frequency of the word appears. Based on the workload, we can see the big picture of public opinion in the 2024 Indonesian presidential election dispute trial both in terms of negative sentiment and positive sentiment.

### 3.6.2 Model Evaluation

Model evaluation classification using SVM and GNB is done by dividing the data into 20% test data and 80% training data on each clean text with literary stemming method and clean text with Nazief Adriani stemming method. Then the data from the three stemming algorithms will be tested and evaluated to determine the value of precision, recall, f1-score and accuracy.

**Table 6.** Model Evaluation

| Stemming Method | Model | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|---|
| **Sastrawi** | **SVM** | **0.90** | **0.91** | **0.90** | **0.911** |
| | GNB | 0.87 | 0.86 | 0.86 | 0.878 |
| Nazief Adriani | SVM | 0.91 | 0.90 | 0.91 | 0.907 |
| | GNB | 0.88 | 0.88 | 0.88 | 0.881 |

In this Table 6, precision measures the accuracy of positive predictions, recall assesses the model's ability to identify all relevant instances, F1-score provides a single metric balancing precision and recall, and accuracy indicates the overall correctness of the model. The results show that the SVM model consistently outperforms the GNB model for both stemming methods, with the Sastrawi stemming method yielding slightly better results overall. Overall, the Support Vector Machine model tends to perform better with accuracy ranging from 90.7% to 91.1%, compared to the Gaussian Naïve Bayes model, with accuracy ranging from 87.8% to 88.1%.

## 4. CONCLUSION

Based on the research conducted, both Gaussian Naïve Bayes (GNB) and Support Vector Machine (SVM) algorithms were evaluated using Sastrawi and Nazief Adriani stemming methods on a dataset of 1998 clean data points. The SVM model with the Sastrawi stemming method achieved the highest accuracy rate of 91.1%, outperforming the GNB model's 87.8%. With the Nazief Adriani method, the SVM model achieved an accuracy rate of 90.7%, while the GNB model reached 88.1%. These results indicate SVM model, particularly when combined with the Sastrawi stemming method, demonstrated the best performance in terms of accuracy, achieving a rate of 91.1%. This finding suggests that the Sastrawi stemming method is more effective for this type of sentiment analysis, and the SVM model is better suited for this task compared to the GNB model. Additionally, the word cloud analysis highlighted the prominence and frequency of certain words, indicating that users on the X platform predominantly expressed negative sentiments regarding the 2024 Indonesian presidential election dispute trial. This trend was evident from the dominance and thickness of negative words in the word cloud, reflecting the general mood and opinion of the public on this matter.

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