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# Media's Role in Reporting 2024 Indonesian Election Fraud

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***Abstract***
*The 2024 Indonesian Presidential Election sparked significant public debate regarding allegations of election fraud. This study investigated public sentiment toward media reporting in response to these fraud allegations on social media platform X. This study employed a quantitative approach with sentiment analysis methods, utilizing three sentiment analysis algorithms: Support Vector Machine (SVM), VADER Sentiment, and Naive Bayes. The research involved collecting tweets related to election fraud, which were then processed using the TF-IDF method to assess the importance of words within the text. Subsequently, the data was classified to identify the sentiment expressed in the tweets. VADER achieved the highest accuracy of 100%, followed by SVM at 92.29%, and Naive Bayes at 90.05%. While most tweets were neutral, negative sentiment was more prevalent in all models. These findings suggested that social media sentiment reflected public opinion on sensitive political issues, providing valuable insights into the discourse on election fraud. The study underscored the need for improving sentiment analysis methods, particularly in addressing data imbalance and the complexities of political sentiment in Indonesia.*

***Keywords****: Election Fraud; Political Discourse; Public Opinion; Sentiment Analysis; Social Media*

**Abstrak**
Pemilihan Presiden Indonesia 2024 menimbulkan kekhawatiran yang signifikan terkait tuduhan kecurangan pemilu. Studi ini menyelidiki sentimen publik pada media di platform media sosial X dalam menanggapi tuduhan penipuan dalam pemilihan 2024. Penelitian ini menggunakan pendekatan kuantitatif dengan metode analisis sentimen dan tiga algoritma analisis sentimen yaitu Support Vector Machine (SVM), VADER Sentiment, dan Naive Bayes. Penelitian ini dilakukan dengan mengumpulkan data berupa tweet terkait dengan kecurangan pemilu, yang kemudian diproses menggunakan metode TF-IDF untuk menilai kepentingan kata-kata dalam teks, dan selanjutnya dilakukan proses klasifikasi terhadap data tersebut untuk mengidentifikasi sentimen yang terkandung dalam tweet-tweet tersebut. Hasil penelitian menunjukkan bahwa VADER mencapai akurasi tertinggi sebesar 100%, diikuti oleh SVM (92,29%) dan Naive Bayes (90,05%). Meskipun sebagian besar tweet bersifat netral, sentimen negatif lebih dominan di semua model. Temuan ini menunjukkan bahwa sentimen media sosial mencerminkan opini publik terhadap isu politik yang sensitif, memberikan wawasan penting dalam wacana terkait kecurangan pemilu. Studi ini menekankan perlunya peningkatan metode analisis sentimen, khususnya dalam mengatasi ketidakseimbangan data dan kompleksitas sentimen politik di Indonesia.

**Kata Kunci:** Analisis Sentimen; Kecurangan Pemilu; Opini Publik; Wacana Politik; Media Sosial

## INTRODUCTION

The year 2024 is poised to host Indonesia's largest democratic event, marking the conclusion of the presidential and vice-presidential term from 2019–2024 (Vonega et al., 2022). This event involves highly favored individual and party-nominated candidate combinations, with active discussions on social media platforms like X, alongside real-world observations (Ardiansyah, 2019). The 2024 election significantly shapes the country's political landscape, where media plays a pivotal role in covering potential election fraud amid rising public awareness (Elislah, 2023).

Media coverage is crucial for shaping public perceptions of democracy, yet it often faces criticism for fostering political cynicism by emphasizing scandals over substantive governance (Elislah, 2023). Despite this, media remains essential as a primary information source, especially during elections, with online platforms disseminating details about election organizers and candidates to enhance transparency and voter participation (Hendriyanto et al., 2023).

The research problem centers on the gap between conventional media and social media in addressing election integrity. While conventional media is tasked with providing accurate, fair, and transparent information to monitor democratic processes, social media, particularly X, has dominated public discourse on election fraud in the digital age.

X serves as a primary forum for opinion sharing, support, or disapproval, offering users and candidates a platform to reach wide audiences (Aletti et al., 2021; Nurfaizah Prawitasari & Fathuzaen, 2018). However, this shift highlights tensions, as social media can amplify unverified information, potentially undermining trust in traditional media's watchdog role.

Previous studies on sentiment analysis in elections have limitations in methods and scope. For instance, Awwalin et al., (2024) used manual data collection from posts and comments, which restricted handling of large-scale data and reduced diversity. Similarly, Yunanto et al. (2024) focused on media narratives and perceptions among specific demographics, like students, limiting broader insights. This study addresses these gaps by employing automated machine learning for data crawling, enabling analysis of larger, more diverse datasets from social media.

This study aims to examine how social media sentiment reflects public perception toward media coverage of election fraud during the 2024 Indonesian Presidential Election. By applying sentiment analysis via tools like VaderSentiment and SVM algorithms on crawled data from X, it categorizes opinions into positive, neutral, and negative sentiments, providing insights into public views on media as a democratic watchdog (Pokharel, 2020; Hasan et al., 2021).

The research contributes to understanding media framing's impact on public opinion, offers recommendations for improving coverage quality on sensitive topics, and supports policymakers in enhancing transparency and accountability. It also advances sentiment detection algorithms for political issues, potentially reducing conflicts from biased reporting, while acknowledging limitations in machine learning interpretations due to subjectivity (Ramesh, 2021; Hidayat et al., 2021).

Future work could incorporate bigrams, trigrams, and varied vectorization for better contextual accuracy (Hasan et al., 2021). Overall, this study enriches research on public opinion dynamics in complex information flows, guiding media integrity and democratic processes (Diyasa et al., 2021).

These findings underscore the media's pivotal role in upholding democratic integrity by fostering transparent and accountable reporting on election fraud, which is essential for maintaining public trust in Indonesia's political processes. However, the rise of algorithmic-driven social media platforms introduces significant challenges to political communication, such as the proliferation of echo chambers and misinformation that can deepen societal polarization and erode institutional credibility. To mitigate these issues, promoting digital literacy among the public is crucial, empowering individuals to critically assess information sources and engage more responsibly in online discourse. Ultimately, by addressing these communicative dynamics, this research highlights the need for collaborative efforts between media, policymakers, and citizens to strengthen democratic resilience in an increasingly digital era.

## METHOD

This study employed a quantitative approach to objectively measure public opinion through numerical data, bridging computational methods with communication studies to explore how digital sentiments reflect democratic discourse. By using Natural Language Processing (NLP) algorithms, sentiments in social media texts were classified into positive, negative, or neutral categories and analyzed statistically. This method not only processes large-scale data, such as thousands of social media comments, but also provides a representative overview of public perceptions in the context of digital democracy. Furthermore, the quantitative results can be visualized in graphs or tables, enabling data-driven insights into how media coverage influences electoral integrity and public trust. The stages of the research carried out can be explained as follows.

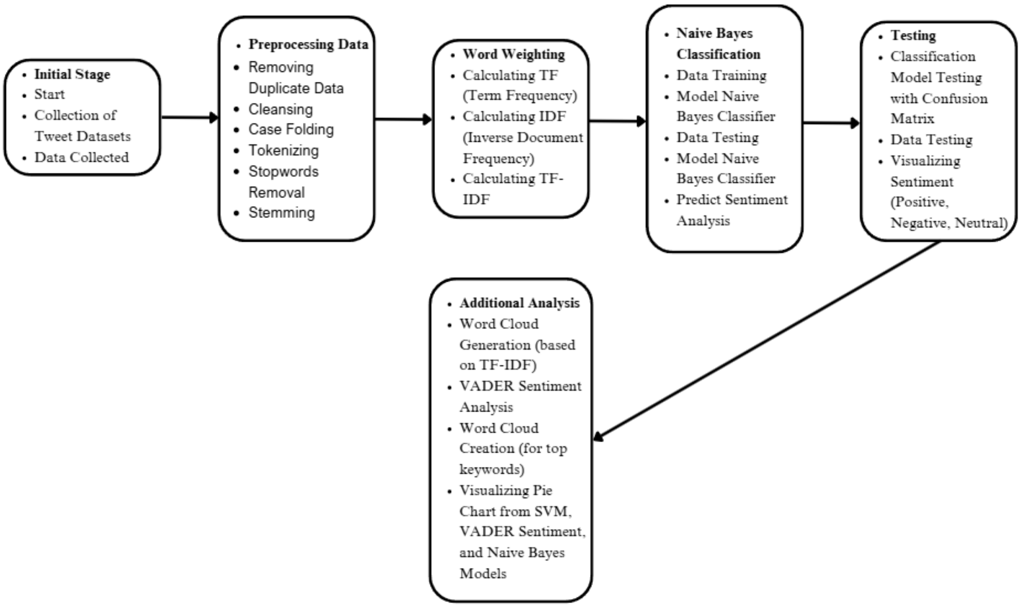


Figure 1. Research Methodology
(Source: Research Result, 2024)

Figure 1 illustrates the first process, called Crawling, where data consists of tweets collected directly from the social media platform X. Data retrieval was conducted via a crawling process using a simple Python-based program in Google Colab (Putri et al., 2020). Initial keywords like “Media Pilpres Kecurangan (Presidential Election Fraud Media),” “Media Pemilu Kecurangan (Election Fraud Media),” “Pelaporan Pemilu Media (Election Media Reporting),” and “Manipulasi Informasi Pemilu (Election Information Manipulation)” did not yield the minimum expected data due to collection constraints (targeting 400–1000 items). Broader keywords, such as “Media Curang Pilpres (Presidential Election Fraud Media)” and “Media Curang Pemilu (Election Fraud Media),” were then used, successfully gathering 2,125 Indonesian-language posts from February 12, 2024, to April 12, 2024. Data was randomly sourced from personal X accounts and online media reports (Khatami, 2021).

The second process, Preprocessing Data, involves four stages to refine the dataset for analysis. First, opinions in the X database are selected to focus solely on the topic “Peran Media dalam Kecurangan Pemilu (The Role of Media in Election Fraud).” Next, cleaning removes irrelevant elements like emoticons, hashtags, links, and usernames to reduce noise. Normalization corrects non-standard spellings for consistency (Buntoro, 2018). Detailed steps include eliminating duplicate data to ensure accuracy and avoid bias; cleansing text by removing symbols; converting all text to lowercase for uniformity; tokenization, which breaks text into words for easier processing; stopword removal, eliminating common words like "dan" (and) or "yang" (that) that add little meaning; and lemmatization/stemming, simplifying words to their root forms to streamline analysis. These steps prepare the data for sentiment classification, highlighting how computational tools can uncover patterns in public discourse on media's role in elections.

The third process, Weighting, uses TF-IDF (Term Frequency-Inverse Document Frequency) to assign importance to words in text categorization, aiding algorithms like Naive Bayes, NLTK, and SVM.

TF-IDF balances word frequency in a document with its rarity across the dataset, helping identify key terms in social media discussions. This method supports probabilistic calculations in Naive Bayes and numerical conversions in SVM, making it effective for analyzing political sentiments (Ramos, 2003). Accuracy is evaluated using metrics like precision, recall, and F1-score, demonstrating TF-IDF's reliability in categorizing text data efficiently.

The fourth process, Classification, follows TF-IDF weighting, employing the Naive Bayes method for text categorization. This probabilistic approach uses weighted features to classify documents into categories like positive, neutral, or negative sentiments, assuming feature independence for simplicity. Naive Bayes performs well in text analysis, comparable to more complex methods (Joachims, 1998), and is particularly suited for social media data where quick, scalable classification reflects public opinions on electoral issues.

The final process, Visualization, compares data with sentiment labels on media's role in 2024 election fraud from social media and personal accounts. Sentiment analysis reveals public polarity—positive, neutral, or negative—using tools like Naive Bayes, NLTK, SVM, and VADER sentiment, which applies a lexicon-based approach to assess emotional tone. Visualizations such as bar charts and word clouds simplify understanding of public views, though subjectivity in text data means interpretations are contextual (Bhoir & Jayamalini, 2021; Kurniawan & Fatulloh, 2017). This bridges computational analysis with communication insights, showing how digital sentiments mirror democratic engagement.

Justification for selecting algorithms: Only three models (Naive Bayes, NLTK, and SVM) were compared due to their proven effectiveness in handling text-based social media data, balancing simplicity and accuracy for large-scale analysis. Naive Bayes offers probabilistic efficiency for sentiment polarity, NLTK provides linguistic processing for Indonesian contexts, and SVM excels in classification boundaries, making them relevant for analyzing socio-political data in Indonesia, where diverse languages and cultural nuances influence public discourse (e.g., as seen in election-related sentiments).

Ethical considerations in social media research: This study adhered to ethical guidelines for digital communication research, focusing on publicly available data from X to respect user privacy. No personal identifiers were collected, and data was anonymized during preprocessing, aligning with principles of informed consent and data minimization (Markham & Buchanan, 2012). This ensures responsible handling of user-generated content in the context of democratic surveillance, avoiding exploitation of private accounts while promoting transparency in media studies.

## RESULTS AND DISCUSSION

### Evaluation of the Sentiment Analysis Model Based on the Confusion Matrix

Based on the testing and calculations, the following are the results and discussions that include the performance of the Naive Bayes and SVM models based on the testing data and the resulting sentiment analysis. The calculations and visualizations in the confusion matrix section do not use the VADER model. This is because VADER is a rule-based method relying on dictionaries and rules, without going through the training process from labeled data in Naive Bayes and SVM. Even though VADER can be used, the resulting scores should be converted into discrete classes with a certain threshold leading to inaccuracies in more complex classifications.

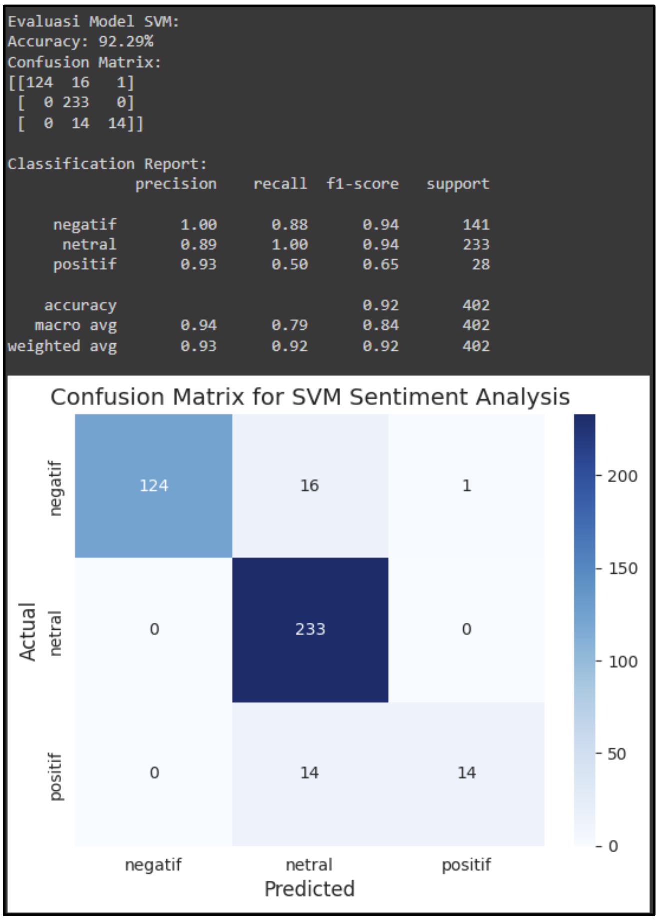


Figure 2. SVM Confusion Matrix Results
(Source: Research Result, 2024)

The confusion matrix with the SVM model used on data with three categories shows very good performance, specifically in the negative and neutral classes. Evaluation metrics such as precision, recall, and f1-score for both classes are high, with an overall accuracy of 92%. The negative class has a precision of 1.00 and a recall of 0.88, while the neutral class has a perfect recall of 1.00 with a precision of 0.89. However, the performance in the positive class is less than optimal, with a recall of only 0.50 and an f1-score of 0.65. This result may be due to the imbalance in the amount of data, where the positive class only has 28 samples less than others.

Based on the confusion matrix, the model tends to misclassify the positive class as neutral. Steps such as data balancing through oversampling, using a more complex model, or hyperparameter tuning can be considered to improve performance, specifically in the positive class. However, this model shows good results and can be optimized for more consistent performance across all classes.

**Comparison of Accuracy Among Algorithms for Sentiment Analysis**

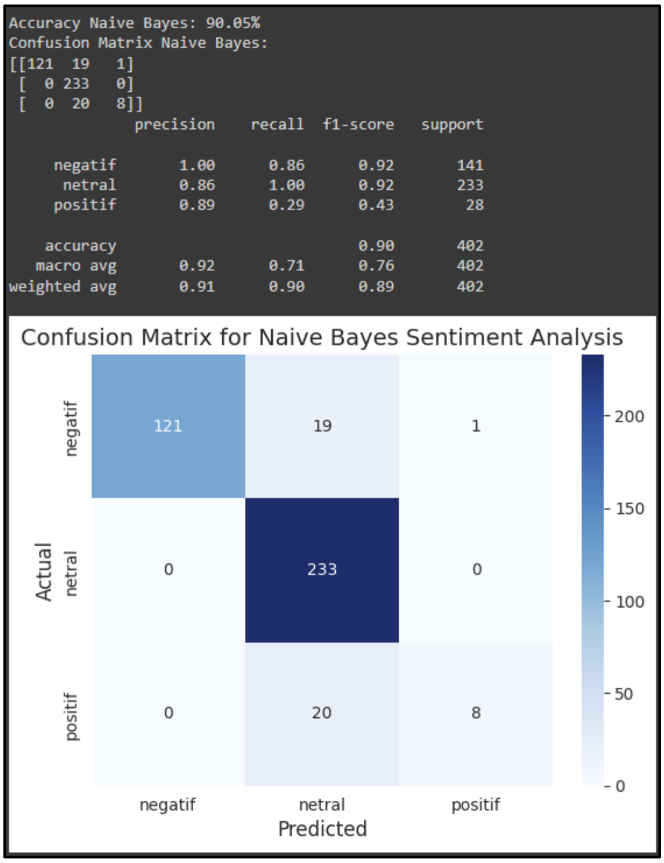


Figure 3. Naive Bayes Confusion Matrix Results
(Source: Research Result, 2024)

Figure 3 shows the results of sentiment analysis using the Naive Bayes model with a confusion matrix and several evaluation metrics. This model can classify data into negative, neutral, and positive. The overall accuracy is 90.05%, slightly lower than the SVM model. The precision for the negative and neutral class is quite high at 1.00 and 0.86 with recall of 0.86 and 1.00, respectively. However, the performance of the model on the positive class is very low with a recall of only 0.29.

The confusion matrix shows that only 8 out of 28 positive class samples were correctly classified, while the remaining 20 were misclassified as neutral. Therefore, Naive Bayes model is bias towards the majority class and has difficulty in recognizing less frequent classes. To improve performance, steps such as data balancing or the use of more sophisticated models can be considered, specifically for the positive class with less data support. This model shows quite good results for the neutral and negative classes, as a viable alternative with some improvements.

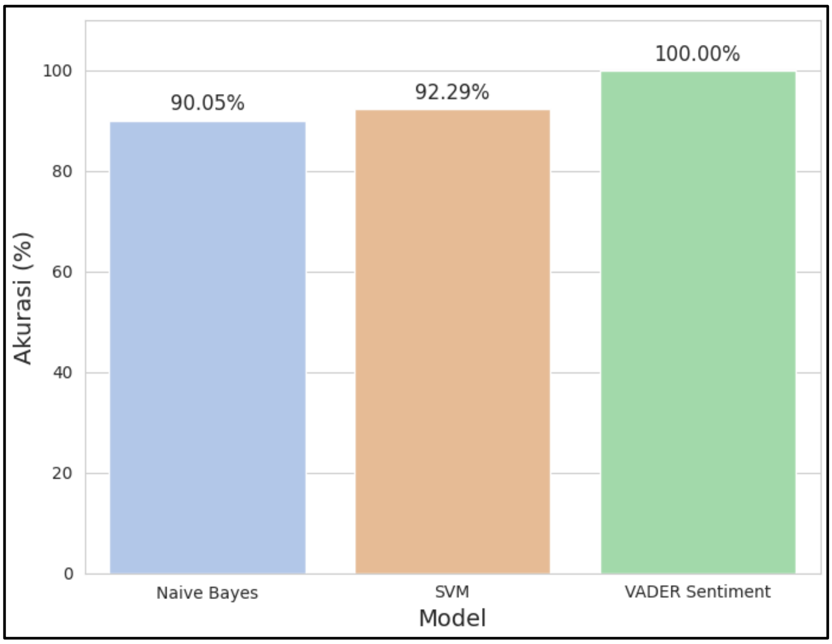


Figure 4. Model Accuracy Comparison
(Source: Research Result, 2024)

Figure 4 shows the accuracy comparison graph based on the confusion matrix results, highlighting the further performance of Naive Bayes, SVM model, and VADER Sentiment. The SVM model is proven to have a higher accuracy (0.92) than Naive Bayes (0.90). This is in line with the results discussed previously, where SVM can classify the negative and neutral classes well despite facing challenges in the positive class. Meanwhile, Naive Bayes shows a bias towards the neutral class and fails to recognize many samples from the positive class, contributing to the lower accuracy.

The difference in accuracy between Naive Bayes, SVM, and VADER in sentiment analysis is due to the respective methods and characteristics. Naive Bayes assumes independence between features, which can reduce accuracy when there is a correlation. Meanwhile, SVM finds the optimal hyperplane to separate classes and is more effective for complex data but sensitive to noise and class imbalance. VADER is very fast and effective for social text when the concept matches the dictionary but the performance decreases on more complex data. This lexicon-based method uses a list of words or phrases with pre-defined polarity scores to measure sentiment in text. These scores determine when a word or phrase conveys a positive, negative, or neutral meaning. Since VADER does not conduct training or testing process, the method is computationally more efficient, but the accuracy depends on the quality of the dictionary used for sentiment analysis. This model provides high accuracy values, approaching 1.00 or 100% when the analyzed data closely matches the words and phrases in the VADER dictionary. This is because VADER matches words with existing polarity scores without having to deal with more complex variability, which occurs in machine learning-based analysis.

Understanding VADER's unique strengths and limitations requires a closer look at its specialized design. VADER (Valence Aware Dictionary and Sentiment Reasoner) is able to achieve high accuracy, up to 100% in some contexts, thanks to its rule-based design that combines a comprehensive lexicon with syntactic and contextual rules. Its lexicon is specifically designed for social media, covering slang, emojis, and colloquial expressions, which improves the understanding of informal language (Suhawni et. al, 2024). VADER's sensitivity to sentiment intensity and polarity allows for accurate interpretation, as seen in a study of sentiment analysis during the Ukraine-Russia war, where it outperformed models such as Naive Bayes and DistilBERT (Anudeepthi et al., 2023). The inclusion of additional pre-processing techniques, such as lemmatization and stop word removal, also further enhances its performance (Garg et al., 2023).

It is important to consider how contextual factors influence the performance of sentiment analysis models. While VADER's superiority is recognized in the context of social media, its performance may vary depending on the dataset and type of text analyzed. In more structured or formal texts, other models such as DistilBERT may provide better results (Hutto & Gilbert, 2014).

This highlights that no single model is universally effective for sentiment analysis, and the choice of approach should align with the specific characteristics of the data and the context of its application.

**Performance of Algorithms and Word Cloud in Uncovering Positive, Negative, and Neutral Sentiment Patterns**

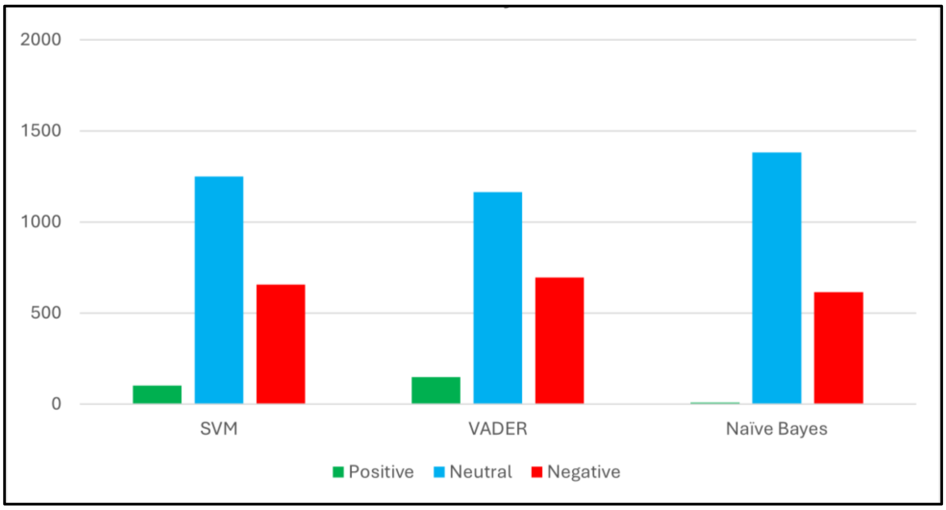


Figure 5. Sentiment Analysis Results
(Source: Research Result, 2024)

Figure 5 shows the results of sentiment analysis from three models, namely SVM (Support Vector Machine), VADER, and Naive Bayes. For the SVM model, this analysis classifies data into three sentiment categories: neutral, negative, and positive. Based on the results, the majority of data falls into the neutral category, with a total of 1,250 data or 62.31%. The number of data classified as negative is 655, equivalent to 32.65%. Meanwhile, data with positive sentiment is 101, which is 5.03% of the total data. For the VADER model, the analysis results are also divided into three sentiment categories, namely neutral, negative, and positive. The number of tweets included in the neutral category is the largest at 1,164 tweets, representing 58.03% of the total data. This is followed by the negative category with a total of 695 tweets or 34.65%. The number of tweets included in the positive category is 147, which is 7.33% of the total analyzed.

In the Naive Bayes model, sentiment analysis shows the same three classes, namely neutral, negative, and positive. Based on the graph, the majority of data is classified as neutral with a total of 1,382, which is equivalent to 68.89%. A total of 615 and 9 data, or 30.66% and 0.45% are categorized as negative and positive, respectively.

The three models show the dominance of the neutral class, while the number of data in the positive category is relatively low. This dominance reflects the complexity of the issues faced by society, where many people feel the need to be careful and do not want to take a clear position on the news circulating. This may show uncertainty about election fraud, where people are caught between acknowledging the problem and remaining objective. Additionally, the significant level of negative emotion suggests skepticism due to doubts about the credibility of media reporting. This trend implies that the media has to exercise greater caution and accountability when disseminating information.

From a communication perspective, the dominance of neutral sentiment can be interpreted through the lens of agenda-setting theory (McCombs & Shaw, 1972), which posits that media influences public opinion by highlighting certain issues. In this case, the prevalence of neutral sentiments may indicate that media coverage of election fraud has created an agenda where audiences are aware of the issue but refrain from strong opinions, possibly due to perceived risks of polarization or misinformation. Meanwhile, the high negative sentiment aligns with the spiral of silence theory (Noelle-Neumann, 1974), where individuals with dissenting views (e.g., skepticism toward media) may feel isolated and thus express negativity more openly, while others remain silent to avoid conflict. This pattern reflects a broader crisis of media distrust, where public perceptions of media legitimacy are eroded, potentially undermining democratic processes by fostering cynicism toward electoral integrity (Tsfati & Cappella, 2003). Overall, these findings highlight how sentiment analysis not only measures algorithmic accuracy but also reveals the communicative dynamics of media framing and audience perception, underscoring the need for media to promote transparency and accountability to rebuild trust in Indonesia's democratic discourse.

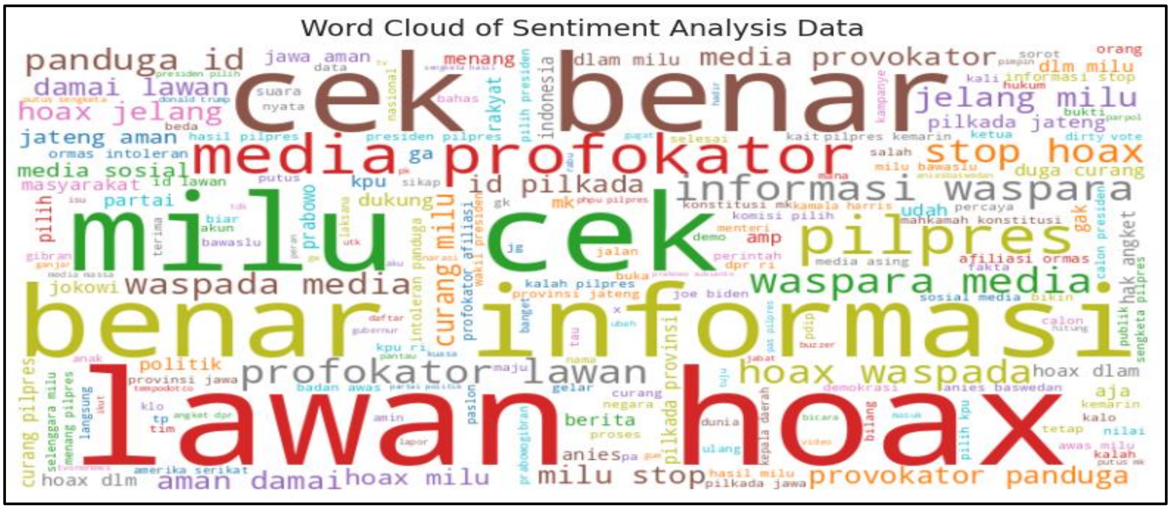


Figure 6. Word Cloud
(Source: Research Result, 2024)

The frequency of words in sentiment analysis about the 2024 Presidential Election and reporting of fraud is shown in Figure 6 on the Word Cloud. Predominant words such as "cek (check)", "benar (true)", "lawan (fight)", "hoax", and "informasi (information)" show the importance of confirming information and combating false information. Words, including "media", "provokator (provocateur)", and "waspada (alert)", reflect popular worries about the manipulation of information during election. Since hoaxes are a hot issue on social media, the word cloud lends credence to the idea that media significantly influences the views of the public on election fraud.

Sentiment analysis shows the necessity of X users to comprehend news reports about fraud in the 2024 presidential election. Therefore, public skepticism of media coverage is reflected in the prevailing neutral attitude even in the large information spreading. This represents the attempts to maintain objectivity while evaluating complicated matters. The high negative sentiment level suggests a profound mistrust of the validity of the voting process and media. According to the tendency, media should exercise greater caution and accountability when disseminating information, particularly sensitive issues such as election fraud. The results show the significance of media in enhancing public trust in addition to offering insight into the new sentiment patterns. The word cloud analysis shows that the public is focused on confirming information. According to the analysis, there is a need to consistently promote raising public awareness of the significance of confirming information and combatting hoaxes in the digital public sphere. Media are expected to increase transparency and accountability in the reporting to reduce skepticism among the public, and strengthen the integrity of the democratic process. These results are reference for policymakers and media practitioners to improve the transmission of information, as well as educate the public about the importance in the context of election.

Building on these findings, several key gaps and opportunities for future research have emerged, particularly in the context of sentiment analysis during the 2024 Indonesian Presidential Election. These gaps highlight areas where new approaches could further enhance our understanding of public sentiment in political discourse.

Research on sentiment analysis related to the 2024 Indonesian Presidential Election reveals several gaps in existing studies, which can provide new directions for future research and improve the understanding of sentiment analysis in a political context. One of the main gaps found is the performance of the algorithms used in sentiment analysis. Studies such as those conducted by Hananto et al. and Alfonso et al. show the effectiveness of the Support Vector Machine (SVM) algorithm, but they do not conduct a comparative analysis with other algorithms such as VADER in the context of reporting election fraud (April et al., 2023; Alfonso & Rarasati, 2023). This opens up opportunities for further research comparing various algorithms in analyzing political sentiment, especially in more complex situations, such as discussing election fraud. In addition, most previous studies have focused on Twitter data, while combining data from various social media platforms can provide a more comprehensive picture of public sentiment (Kottala et al., 2024). Cultural and linguistic nuances also need to be considered in sentiment analysis. Existing studies often ignore these factors, which influence how sentiment is interpreted in Indonesia. Joseph (2024) emphasized the need to use advanced NLP (Natural Language Processing) techniques to capture the cultural subtleties that exist in political discussions in Indonesia. In addition, real-time analysis is an area that still has a large gap, even though the application of this technique can improve the responsiveness of media reporting during elections and provide more actual insights into public sentiment (Joseph, 2024). Ethical aspects also need to be considered more deeply, especially related to data privacy. The use of social media data for sentiment analysis raises important questions about privacy, which to date have been under-explored in existing research. Future research should develop bias mitigation strategies and adhere to ethical principles related to data privacy in the collection and analysis of social media data (Joseph, 2024).

Overall, although the current research provides valuable insights into sentiment analysis, there is a lack of discussion of the dynamic nature of social media discourse, especially in a charged political environment. This suggests the need for continued research that adapts the methodology to the evolving social media landscape, and pays attention to deeper ethical and contextual dimensions.

The novelty of this study was based on the comparative approach that combined three sentiment analysis algorithms, namely Naive Bayes, SVM, and VADER, to analyze public sentiment on social media platform X regarding news of fraud in the 2024 Indonesian Presidential Election. Unlike previous research (Majbur et al., 2024) on the same topic, which collected data through X and used only one algorithm, Naïve Bayes, this study provided broader insights by comparing the performance of various algorithms in detecting sentiment in data originating from social media that was highly dynamic and constantly evolving. By applying this comparative approach, the study also emphasized the need to refine sentiment analysis methods to better capture the nuances in rapidly changing online environments. In addition, this study also highlighted the importance of accuracy in the classification of sentiment related to sensitive political issues, addressing the unique challenges posed by social media discourse, as well as contributing to the development of a more adaptive sentiment analysis methodology to handle data imbalances and the cultural nuances within the Indonesian context.

As explained in Social Polarization Theory, society can become divided into groups with opposing views as a result of exposure to biased information. The findings of this study suggested that social media played a significant role in reinforcing such polarization. Polarization on social media was often reinforced by algorithms that pushed users into echo chambers, digital environments where they were only exposed to information that aligned with their preferences (Sunstein, 2001). In the political context of elections, polarization could be triggered by narratives that exploited specific issues, such as economics, culture, and infrastructure, which resonated with local community interests (Iyengar et al., 2012). This study demonstrated that such polarization not only affected individuals' perceptions of political issues but also shaped social relationships among groups with differing sentiments.

With these findings, this study offered valuable insights into the influence of social media on public perceptions of political integrity, especially when addressing allegations of election fraud. As such, it served as an important reference for understanding the broader implications of social media's role in shaping democratic processes and future research on the topic.

## CONCLUSION

Based on the research results, the VADER model showed the best performance in sentiment analysis compared to SVM and Naive Bayes. These three models indicate the dominance of neutral sentiment with a percentage of between 58.03% and 62.31%. However, VADER and SVM are more effective in identifying negative sentiment than positive sentiment. Negative sentiment was detected with a significant percentage of between 30.66% and 34.65%, while positive sentiment was very minimal, only ranging from 0.45% to 7.33%. This finding shows that the discourse related to reports of election fraud is dominated by neutral or negative sentiment. A neutral attitude reflects public uncertainty about the information conveyed by the media, while high negative sentiment indicates concerns about the credibility of the report. Therefore, a deeper understanding and further research are needed to identify the influence and impact of this sentiment pattern. This is important so that the public is increasingly aware of the importance of verifying information independently, so that it can reduce losses arising from the spread of inaccurate or misleading information.

These findings reveal that the dominance of neutral and negative sentiment reflects the fragility of public trust in media. In the context of communication and media, this pattern underscores the media's critical role in safeguarding democratic integrity by promoting accurate and balanced reporting on sensitive issues like election fraud. However, political communication in the algorithmic era faces significant challenges, such as the amplification of echo chambers and misinformation through social media platforms, which can exacerbate polarization and erode institutional legitimacy. To address this, enhancing public digital literacy is essential, empowering audiences to critically evaluate sources and navigate complex information landscapes. Ultimately, strengthening media transparency and digital literacy is crucial to sustain democratic communication in Indonesia.

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