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# Sentiment Analysis for the 2024 DKI Jakarta Gubernatorial Election Using a Support Vector Machine Approach

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**ABSTRACT**

This study analyzes public sentiment regarding candidates in the 2024 DKI Jakarta Gubernatorial Election utilizing a Support Vector Machine (SVM) approach. Recognizing the pivotal role of social media, particularly Twitter, in shaping public opinion, the research addresses the challenges of processing large volumes of unstructured data. Through systematic data preprocessing and feature extraction, the SVM model was applied, achieving a sentiment classification accuracy of 70%. The analysis revealed a distribution of sentiments where 36.1% of comments were positive, 33.4% negative, and 30.5% neutral. These findings illustrate the complexities of public discourse surrounding key political events, highlighting the model's efficacy and the nuances of sentiment detection. Moreover, discussions on model limitations elucidate areas for enhancement, suggesting future avenues including the adoption of more sophisticated algorithms and improved data processing techniques. This research contributes to the understanding of voter sentiment dynamics in a significant electoral context, providing insights that may assist campaign strategies and political analyses in Indonesia.

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## I. INTRODUCTION

The gubernatorial election is an important part of the democratic system because the position of the governor plays a strategic role as a leader at the provincial level. The governor is responsible for the implementation of governance, development, and public services in their region [1]. The sustainability of the governance process and the efficiency of conducting elections depend on the regulations established in the legislation. The election of the candidates for governor and deputy governor of DKI Jakarta in 2024 is a political event that has garnered widespread attention from the public, considering the strategic position of DKI Jakarta as the capital of Indonesia and the economic center of the country. As one of the most densely populated cities, public opinion regarding regional leadership candidates is very diverse and spreads quickly through social media, especially via the social media platform Twitter, now known as X [2].

Data from X is rapidly evolving, making manual analysis increasingly difficult. Every moment, thousands of tweets may emerge related to electoral issues, presenting many challenges in efficiently processing big data. Many X users employ informal language or abbreviations, complicating text analysis. Additionally, the amount of unstructured data requires a feature extraction process to be usable by machine learning algorithms [3].

The implementation of the SVM algorithm in sentiment analysis requires a feature extraction process such as TF-IDF (term frequency-inverse document frequency), which is commonly used to convert text into meaningful numerical formats. The algorithm often used in sentiment analysis is Naïve Bayes, known for its efficiency and simplicity, but it is less effective for complex data. Another method is Random Forest, which offers high accuracy but has disadvantages in processing speed for large datasets. Therefore, in the sentiment analysis of the gubernatorial and deputy gubernatorial candidates in DKI Jakarta, the author chose the SVM method [4].

Several previous studies have used SVM in political sentiment analysis in Indonesia. For example, research by [5] shows that SVM achieved an accuracy of 83% in analyzing public sentiment on Twitter after the 2024 Presidential Election, higher than the 70% accuracy achieved in this study. This difference is attributed to variations in datasets, preprocessing methods, or feature extraction techniques used. Therefore, this study needs to conduct a more in-depth comparison to understand the factors influencing these differences.

With this addition, the research will have a stronger theoretical foundation, and readers can understand how the results obtained compare with previous studies. The aim of this research is to ensure the alignment between the events that have occurred in the election of candidates for governor and deputy governor of DKI Jakarta and the scientific analysis results using the Support Vector Machine (SVM) algorithm [6]. This study also aims to evaluate whether the methods used, including the SVM algorithm, can accurately reflect the realities of the events that occurred, thereby providing validation for the scientific approach applied in analyzing the election results. Although deep learning models like BERT or LSTM often provide better performance in social media sentiment analysis, SVM remains a valid choice in certain situations. Considerations such as competitive performance on specific datasets, computational efficiency, and ease of interpretation can support the selection of SVM as an analytical method.

## II. Metode

This research applies the Support Vector Machine (SVM) algorithm in an effort to analyze sentiment in comments on the X platform regarding the election of candidates for Governor and Deputy Governor of DKI Jakarta 2024 [7]. The stages of the research process can be found in Figure 1.

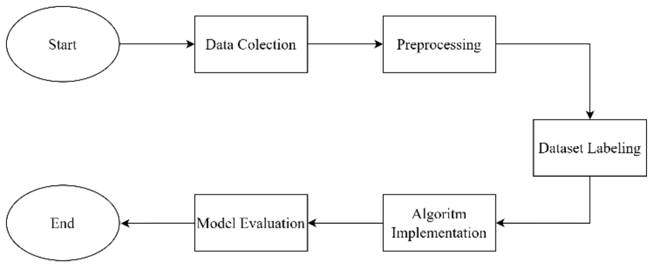


Figure 1. Stages of the Research Process

### A. Data Collection

The data analyzed in this research consists of tweets from X users in Indonesia that contain keywords related to the Jakarta Governor candidates. This analysis can provide valuable insights for campaign teams regarding public perceptions that need to be improved or strengthened.

### B. Preprocessing

Preprocessing is the stage of data analysis aimed at cleaning and preparing raw data to be more structured and ready for analysis or modeling. In the preprocessing stage, six steps are carried out as follows [7]:

1) *Cleaning:* The Cleaning stage is carried out to facilitate the process of managing text data. This stage aims to evaluate the quality of data that does not conform to the required format, with the goal of obtaining high-quality data [8]. The cleaning stages can be found in Table 1.

TABLE I
CLEANING RESULTS

| ***Text*** | ***Cleaning*** |
|---|---|
| Jakarta Governor Candidate number 1, Ridwan Kamil (RK), once again voiced his plan to build Disneyland in the Thousand Islands during the 2024 Pilkada debate on Sunday (27/10/2024). | Jakarta Governor Candidate Ridwan Kamil (RK) once again voiced his plan to build Disneyland in the Thousand Islands during the Pilkada debate on Sunday. |

*Case Folding:* Converting all letters in the text to lowercase. This stage it can be seen in the table 2 supports the process of text discovery and management, as using lowercase letters ensures consistency in capitalization throughout the text [9].

TABLE II
CASE FOLDING RESULT

| ***Text*** | ***Cleaning*** |
|---|---|
| jakarta governor candidate ridwan kamil (rk) once again voiced his plan to build disneyland in the thousand islands during the pilkada debate on sunday. | Jakarta governor candidate Ridwan Kamil (RK) once again voiced his plan to build Disneyland in the Thousand Islands during the Pilkada debate on Sunday. |

2) *Tokenizing:* Tokenization generally breaks a sequence of characters in a text into word units by identifying specific elements that can be recognized as word separators or not [9]. The tokenization process can be seen in Table 3.

TABLE III
TOKENIZING RESULT

| ***Text*** | ***Cleaning*** |
|---|---|
| jakarta governor candidate ridwan kamil rk once again voiced his plan to build disneyland in the thousand islands during the pilkada debate on sunday | ['candidate', 'governor', 'dki', 'jakarta', 'number', 'order', 'ridwan', 'kamil', 'rk', 'again', 'voiced', 'plan', 'development', 'disneyland', 'in', 'islands', 'thousand', 'in', 'debate', 'pilkada', 'sunday'] |

3) *Normalization:* Normalization is the process of converting inconsistent words into their standard form, This process can be seen in Table 4.

TABLE IV
NORMALIZATION RESULT

| *Text* | *Cleaning* |
|---|---|
| Jakarta Governor Candidate Ridwan Kamil (RK) once again voiced his plan to build Disneyland in the Thousand Islands during the Pilkada debate on Sunday. | ['candidate', 'governor', 'dki', 'jakarta', 'number', 'order', 'ridwan', 'kamil', 'rk', 'again', 'voiced', 'plan', 'development', 'disneyland', 'in', 'islands', 'thousand', 'in', 'debate', 'pilkada', 'sunday'] |

*4) Stopwords Removal:* Removing common words that are not relevant to the text. These words usually function as connectors or modifiers but do not have significant meaning [10], The process of removing stop words can be seen in Table *5.*

TABLE V
NORMALIZATION RESULT

| *Text* | *Cleaning* |
|---|---|
| ['candidate', 'governor', 'dki', 'jakarta', 'number', 'order', 'ridwan', 'kamil', 'rk', 'again', 'voiced', 'plan', 'development', 'disneyland', 'islands', 'thousand', 'debate', 'pilkada', 'sunday'] | ['candidate', 'governor', 'dki', 'jakarta', 'number', 'order', 'ridwan', 'kamil', 'rk', 'voiced', 'plan', 'development', 'disneyland', 'islands', 'thousand', 'debate', 'pilkada', 'sunday'] |

*5) Streaming:* Summarizing words into their root form by removing affixes. This stage utilizes the Sastrawi library for stemming [11], The stemming process can be seen in Table 6.

TABLE VI
NORMALIZATION RESULT

| *Text* | *Cleaning* |
|---|---|
| ['calon', 'gubernur', 'dki', 'jakarta', 'nomor', 'urut', 'ridwan', 'kamil', 'rk', 'suara', 'rencana', 'bangun', 'disneyland', 'pulau', 'seribu', 'debat', 'pilkada', 'minggu'] | ['calon', 'gubernur', 'dki', 'jakarta', 'nomor', 'urut', 'ridwan', 'kamil', 'rk', 'suara', 'rencana', 'bangun', 'disneyland', 'pulau', 'seribu', 'debat', 'pilkada', 'minggu'] |

## *C. Labelling Sentimen*

Sentiment labeling is done manually, where this process assigns labels to text data collected from the X platform. Manual labeling allows the author to understand context and nuances that are difficult for automated systems to capture [12]. Table 7 contains the sentiment labeling that was done manually.

TABLE VII
LABELING RESULT

| **Candidate_name** | ***Full_text*** | **Sentiment label** |
|---|---|---|
| Ridwan kamil | Ridwan Kamil held a dinner with Anies. | Neutral |
| Dharma | I swear it would be better to eat a baby than a dharma shaman | Negative |
| Pramono | Mas Pram or Bang Doel is indeed suitable to be governor of DKI Jakarta | Positive |

## *D. Fiture Extraction (TF_IDF)*

In the sentiment analysis of the 2024 Jakarta Governor and Deputy Governor candidates, the feature engineering implemented is TF-IDF (Term Frequency-Inverse Document Frequency), a statistical method applied in Natural Language Processing and Text Mining to represent text in numerical form [13].

## *E. Train SVM Model*

The process is carried out to learn patterns and relationships between input data and sentiment labels (positive, negative, neutral). The training results show that the model succeeded in making predictions with an accuracy rate of 70%, which means 7 out of 10 test data were successfully classified correctly. This accuracy shows an initial picture of the model's performance in classifying sentiment data [14]. Figure 2 shows the accuracy results of the sentiment labeling performed.

```
Akurasi: 0.70
Laporan Klasifikasi:
              precision    recall  f1-score   support

     positif       0.67      0.67      0.67         3
      netral       0.50      0.33      0.40         3
     negatif       0.80      1.00      0.89         4

    accuracy                           0.70        10
   macro avg       0.66      0.67      0.65        10
weighted avg       0.67      0.70      0.68        10
```

Figure 2. SVM Accuracy

The image above shows an accuracy level of 70% obtained from the results of training data with a 70:30 division using the SVM algorithm. These results show that the model is able to make correct predictions for 7 out of 10 test data accurately.

## *F. Model Evaluation*

Measure a model's performance in completing a specific task. In sentiment analysis using TF-IDF and classification algorithms such as SVM, evaluation metrics such as Accuracy, Pre-cision, Recall, and F1-Score are applied to assess the success of the model [15]. The model performance measurement results can be seen in Figure 3.

```
Accuracy  =  100.0 %
Recall    =  100.0 %
Precision =  100.0 %
F1-Score  =  100.0 %
```

Figure 3. Evaluation Results Using TF_IDF

The figure above shows that the model achieved 100% accuracy, which means it successfully predicted all test data correctly. These results were obtained from dividing the data 70:30 using the TF-IDF method for feature extraction and the SVM algorithm after the data preprocessing process. This trained model is also used to predict sentiment in new tweets that have not previously been processed by the system [16].

## III. RESULT AND DISCUSSION

The sentiment analysis results for the 2024 DKI Jakarta gubernatorial election using the Support Vector Machine (SVM) approach. The evaluation was conducted to measure the model's performance in classifying public sentiment into positive, neutral, and negative categories. This analysis includes evaluation metrics such as accuracy, precision, recall, and F1-score, as well as the use of a confusion matrix to identify the model's weaknesses in distinguishing sentiment categories. Additionally, data visualization in the form of a Word Cloud and sentiment distribution is used to provide a deeper insight into public opinion patterns regarding gubernatorial candidates.

### *A. Sentiment Distribution*

Sentiment distribution is conducted to understand how perceptions or opinions are divided within a dataset. The sentiment distribution in this analysis shows how public opinion regarding the 2024 DKI Jakarta gubernatorial election is categorized into three main categories: positive, neutral, and negative. The sentiment distribution graph can be found in Figure 4.

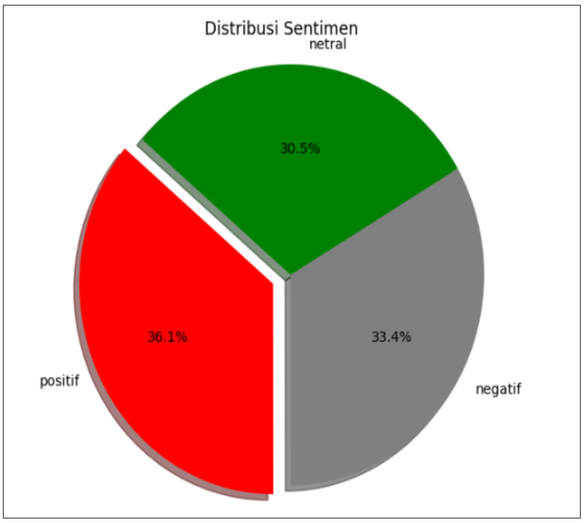


Figure 4. Graf Sentiment Distribution

Based on the classification results using Support Vector Machine (SVM), the sentiment distribution is as follows: Positive Sentiment: 36.1%, Negative Sentiment: 33.4%, Neutral Sentiment: 30.5%. From this distribution, it appears that positive sentiment dominates, indicating a public tendency to express supportive or optimistic opinions toward the gubernatorial candidates. However, the relatively high percentage of negative sentiment (33.4%) indicates criticism or dissatisfaction from a portion of the public. Meanwhile, neutral sentiment (30.5%) suggests a group that provides opinions without a strong inclination toward either positive or negative.

This distribution is also visualized through a Word Cloud and sentiment distribution graphs, which help identify dominant keywords in each sentiment category as well as patterns of public discourse on social media [17].

### *B. Model Evaluation*

To evaluate the performance of the SVM model, metrics such as accuracy, precision, recall, and F1-score were used. The evaluation results can be found in Table 8.

TABLE VIII
MODEL EVALUATION

| Class Sentiment | Precision | Recall | F1-score |
|---|---|---|---|
| Positive | 0.67 | 0.67 | 0.67 |
| Neutral | 0.50 | 0.33 | 0.40 |
| Negative | 0.80 | 1.00 | 0.89 |

The classification performance results with precision, recall, and F1-score metrics reveal several important findings in the sentiment analysis of the 2024 DKI Jakarta gubernatorial election using Support Vector Machine (SVM):

*1)* *Positive Sentiment* has a precision, recall, and F1-score of 0.67. This indicates that the model is fairly good at recognizing and classifying positive opinions, balancing accuracy and the ability to detect this sentiment.

2) *Neutral Sentiment* has a precision of 0.50 and a recall of only 0.33, resulting in an F1-score of 0.40. The low recall value indicates that the model often fails to recognize neutral opinions, leading to many neutral data being classified as positive or negative.

*3)* *Negative Sentiment* performs the best, with a precision of 0.80 and a recall of 1.00, yielding the highest F1-score of 0.89. This indicates that the model is very effective at detecting negative opinions and nearly does not miss any data classified under this category.

Overall, the model's accuracy reached 70%, which means the model is fairly good but still has weaknesses, particularly in classifying neutral sentiment. This performance shows that the model can recognize positive and negative opinions better than neutral ones, which often have more ambiguous contexts.

### C. Confusion Matrix Analysis

The confusion matrix is used to identify the model's weaknesses in classifying data. Table 9 presents the confusion matrix results.

TABLE IX
CONFUSION MATRIX

| Sentiment Class | Pred. Positive | Pred. Netral | Pred. Negatif |
|---|---|---|---|
| Akt. Positive | 4 (TP) | 0 (FN) | 0 (FN) |
| Akt. Neutral | 1 (FN) | 1 (TN) | 1 (FN) |
| Akt. Negative | 0 (FN) | 1 (FN) | 2 (TN) |

From the table above, several weaknesses of the model can be concluded:

1) *The model is quite effective at classifying positive sentiment, with True Positives (TP) totaling 4 cases and no False Negatives (FN).*

2) *Neutral sentiment remains difficult to classify correctly, as there is 1 FN in neutral sentiment classified as positive and another FN classified as negative.*

3) *Negative sentiment has 1 FN classified as neutral, indicating that the model struggles to differentiate between negative and neutral sentiments.*

With this evaluation, it is evident that the model still needs improvement, especially in increasing recall for neutral and negative categories. Employing more advanced text processing techniques, such as word embeddings or deep learning-based models, could help enhance context understanding and improve sentiment classification performance.

### D. Word Cloud

To understand the most frequently occurring words in each sentiment category, a Word Cloud visualization was created:

1) *Positive Sentiment:* Dominant words include "DKI Jakarta," "https," "gubernatorial candidates," "Governor of DKI," "deputy governor," and "Pramono Anung."


Figure 5. Visualisasi Word Cloud Possitive Sentiment

2) *Negative Sentiment:* Frequently appearing words are "DKI Jakarta," "Gubernatorial Candidates," "deputy governor," and "Dharma Pongrekun."


Figure 6. Visualisasi Word Cloud Negative Sentiment

3) *Neutral Sentiment:* Words that appear tend to be descriptive, such as "DKI Jakarta," "gubernatorial candidates," "Pramono Anung," "Ridwan Kamil," and "Dharma Pongrekun."


Figure 7. Visualisasi Word Cloud Neutral Sentiment

### E. Class Imbalance and Solutions

In this analysis, the amount of data for each sentiment class can be seen in Table 10.

TABLE X
CLASS IMBALANCE AND SOLUTIONS

| Sentiment Category | Data Count | Percentage (%) |
|---|---|---|
| Positive | 1,409 | 36,1% |
| Neutral | 1,188 | 30,5% |
| Negative | 1,303 | 33.4% |
| **Total** | **3,900** | **100%** |

Based on the table above, it appears that the data distribution is relatively balanced among positive, neutral, and negative sentiment categories. The largest difference occurs between the positive and neutral classes, with 221 data points (approximately 5.6% of the total dataset).

If the model has low recall in certain classes, several factors may be contributing, including language complexity, similarity between sentiments, and feature imbalance in text representation. Language complexity includes the use of slang, non-standard spelling, or words with ambiguous meanings that can confuse the model in classifying sentiment correctly. Additionally, the similarity between sentiments can pose challenges, especially if an opinion has nuances that are difficult to distinguish between positive, neutral, or negative.

To improve recall, the first step is to enhance data preprocessing, for example, by using lemmatization or stemming to ensure words have uniform base forms, as well as improving text normalization to handle abbreviations and informal words. Additionally, text representation can be enhanced using more advanced methods like word embeddings (Word2Vec, FastText, or BERT) that can better capture word meanings in context compared to TF-IDF. If low recall occurs due to a lack of data in certain classes, a possible solution is to augment the training data through oversampling or data augmentation to help the model better recognize patterns in that class.

From the model side, adjusting the algorithm and hyperparameters can also be a solution, such as trying deep learning-based models like LSTM or Transformer, or tuning SVM parameters for better optimization. If class imbalance is the main cause of low recall, techniques like oversampling (SMOTE) or cost-sensitive learning can be applied to ensure the model does not overly favor the majority class. With these various efforts, it is hoped that recall in specific classes can improve, allowing the model to classify sentiment more accurately and consistently.

### *F. Disucussion*

In this study, the Support Vector Machine (SVM) model achieved an overall accuracy of 70%, with a sentiment distribution characterized by Positive Sentiment: Precision 0.67, Recall 0.67, F1-Score 0.67; Neutral Sentiment: Precision 0.50, Recall 0.33, F1-Score 0.40; and Negative Sentiment: Precision 0.80, Recall 1.00, F1-Score 0.89. A comparative analysis with related research indicates that the findings of this study exhibit lower accuracy than several prior studies. For instance, research conducted by [6] employed both Naive Bayes Classifier and SVM methods for sentiment analysis of the DKI Jakarta gubernatorial election, yielding an impressive accuracy of 87.80%, with Precision at 98.48%, Recall at 87.80%, and F-Measure at 92.64%. Similarly, the study by [5] analyzed public sentiment on Twitter following the 2024 Presidential Election, reporting a Precision of 0.85, Recall of 0.82, F1-Score of 0.83, and an overall accuracy of 0.83.

The discrepancies in results between this study and previous research may stem from several factors. First, the data preprocessing methodologies utilized may significantly influence the quality of input data, as varying techniques for text cleaning and normalization can affect model performance. Second, the selection of features plays a crucial role; employing more relevant features or superior feature extraction techniques can enhance the efficacy of the model. Third, the size and quality of the dataset are pivotal, as the amount of training data and its diversity can directly impact the model's generalization capabilities. Lastly, the differences in context and timing, as sentiment analysis for the DKI Jakarta gubernatorial election was conducted during distinct periods, may have influenced public opinion and the resultant analysis outcomes.

Considering these factors, future research should prioritize refining preprocessing techniques, selecting more appropriate features, and utilizing more representative datasets to bolster the accuracy and performance of models in political sentiment analysis within the Indonesian context.

## IV. CONCLUSION

In this study, sentiment analysis of social media comments was conducted using the Support Vector Machine (SVM) model with TF-IDF feature extraction. The model achieved an accuracy of 70% with a data split ratio of 70:30, revealing that 36.1% of comments were positive, 33.4% negative, and 30.5% neutral. Visualizations, including Word Cloud and sentiment distribution, provided additional insights into public opinion concerning specific candidates.

Despite the satisfactory performance of SVM, the 70% accuracy indicates room for improvement. Factors affecting model performance include noise in the data, informal language, code-mixing with English or local dialects, and common typographical errors in social media text. Additionally, the choice of a 70:30 data split, which did not include a validation set, may limit parameter optimization. This study did not compare the SVM model with other methods, such as Naive Bayes or deep learning techniques like LSTM and BERT, which are known for better contextual understanding. Previous research (Kim et al., 2020) demonstrates that neural network-based models can capture more complex language patterns, presenting promising alternatives for sentiment analysis.

To enhance future sentiment analysis accuracy, several improvements are recommended: employing advanced models like LSTM, BERT, or Transformer-based architectures to better grasp text context; enhancing data preprocessing with slang dictionaries, code-mixing detection, and typo correction to reduce noise; testing alternative data split ratios, such as 80:10:10, for validation and improved generalization; and comparing with other methods such as Naive Bayes, Random Forest, or deep learning to evaluate model effectiveness comprehensively. By implementing these enhancements, future research aims to increase model accuracy and yield more precise and representative sentiment analysis of public opinion on social media.

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