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# Sentiment Analysis Regarding Candidate Presidential 2024 Using Support Vector Machine Backpropagation Based

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**ABSTRACT**

This research has the potential to make an important contribution to the development of computationally-based sentiment analysis, particularly in the political context. Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto, three candidates for the presidency of Indonesia, are examined using a Backpropagation-based Support Vector Machine (SVM) methodology in this study. This approach is used to categorize emotions into three groups: neutral, adverse, and favorable. Between July 1 and July 30, 2023, data on tweets mentioning the three presidential contenders was gathered. After processing the data, SVM was used while lowering the backpropagation process. The study's findings demonstrate that the performance of the model in determining public sentiment is greatly enhanced by the application of backpropagation-based SVM techniques. For each presidential contender, the evaluation was conducted using the f1 score, recall, and precision metrics. The evaluation's findings indicate that while the model struggles to distinguish between favorable and negative feelings toward particular presidential contenders, it performs better when categorizing neutral feelings. The SVM model is more accurately able to identify popular sentiment toward the three presidential candidates when the backpropagation approach is used. The results of the sentiment analysis are also represented by word clouds for each presidential contender, giving an intuitive sense of the words that are frequently used in public discourse. This study sheds light on the possibilities of using Twitter data to analyze political sentiment using the backpropagation-based SVM algorithm.

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## A. INTRODUCTION

Presidential Election is one of the crucial moments in a democratic system, where the people have the right to vote to choose a presidential candidate who is deemed most suitable to lead the country (Curato, 2017) (Rennó, 2020). Presidential elections in Indonesia will be held on 14 February 2024 (Budiharto & Meiliana, 2018). In the presidential election process, public opinion and sentiment about presidential candidates have a very important role in shaping their views and decisions (Karami et al., 2018). An in-depth understanding of the public's views on presidential candidates, especially in relation to potential candidates such as Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto, can provide valuable information for the candidates themselves, the campaign team, as well as the public and the media to understand aspects that need attention in political campaign (Wiyono et al., 2023).

As a result of the development of information technology and social media, the amount of information related to public opinion and sentiment towards presidential candidates has increased and is still growing today (Oliveira et al., 2017). The data covers various aspects, including opinions, supports, criticisms, and complaints from various walks of life, which are often done via Twitter (Kursuncu et al., 2019). However, manual analysis of this large and varied data can be difficult and time-consuming.

Therefore, the existence of computational-based sentiment analysis in the field of natural language processing is very relevant and important in processing large and complex data efficiently (Medhat et al., 2014) (Yang et al., 2021) (Fatimathuzahra et al., 2022). Sentiment analysis techniques can help filter and classify sentiments into 3 classes, namely positive, negative and neutral. It enables a quicker and more accurate assessment of how the general people feels about the presidential contenders Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto (Achmad & Haris, 2023) (Dwinarko et al., 2023).

However, although there are various methods of sentiment analysis that have been developed, it cannot be ignored that a number of previous studies have addressed similar topics. For example, research that discusses sentiment analysis using SVM methods on Twitter data can provide an initial overview of public opinion regarding autonomous cars and Apple products. The results of such research can provide valuable information for companies, policymakers or marketers to understand the sentiments expressed by users on social media platforms (Ahmad et al., 2017). In addition, there are also studies that apply SVM in sentiment analysis on Twitter data by producing innovative approaches to improve the accuracy and sustainability of the model (Han et al., 2020). However, the use of SVM in sentiment analysis requires optimization and adjustments in order to provide accurate and representative results (Elgeldawi et al., 2021). The backpropagation-based approach that has been applied to the SVM method, in particular, has improved the model's ability to recognize public sentiment toward the three Indonesian presidential candidates 2024 (Manek et al., 2017)(Ahmad et al., 2017). Through this approach, it is hoped that a SVM model that is more adaptive and has better predictive ability in classifying sentiments related to presidential candidates can be produced (Liu et al., 2021) (Chen et al., 2017) (Ghiassi & Lee, 2018).

Taking into account the above phenomena, this study aims to develop a sentiment analysis machine learning model based on SVM with the backpropagation method to analyze public sentiment regarding presidential candidates Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto who have the potential to run for the 2024 presidential election. This research has practical relevance, because it can provide a comprehensive view of public opinion and sentiment towards the three presidential candidates with 3 classes namely positive, negative and neutral, thus helping candidates and campaign teams in designing campaign strategies that are more effective and responsive to people's aspirations. In addition, this study retrieves information by collecting Twitter data using the Python programming language.

Theoretically, this research has the potential to make an important contribution to the development of computational-based sentiment analysis, especially in the political context (Rintyarna, 2021). By utilizing the Support Vector Machine, this research produces matrix performance improvements, including F1-Score, precision, memory, and accuracy in analyzing sentiment and provides in-depth and comprehensive understanding. By integrating back-

progation this research seeks to provide a deeper understanding of the effectiveness and efficiency of the model in classifying sentiment on complex political data (Fatimathuzahra et al., 2022).

## B. METHODS

This study discusses the findings of sentiment analysis of the three presidential candidates of the Republic of Indonesia who are running for office in 2024 using the Backpropagation-based Support Vector Machine (SVM) technique. Figure 1 will explain the flow of the method used in this study.

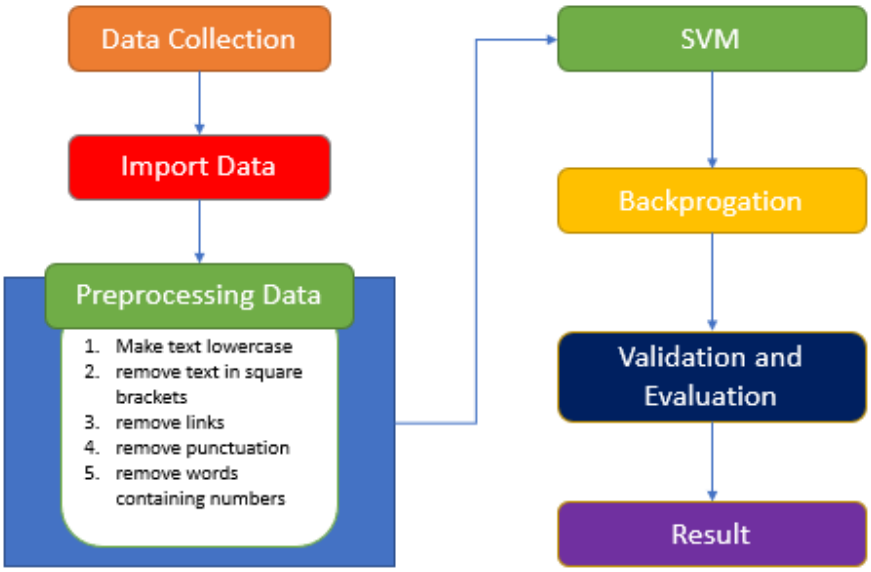


**Figure 1.** Flow Method

### 1. Data Collection

The tweets from 1 July 2023 to 30 July 2023 were collected to create the dataset used in this study (Sugiyarto et al., 2021). There are 3 candidates competing in the 2024 Indonesian presidential election, namely Anies Baswedan, Ganjar Pranowo and Prabowo Subianto. Of these three candidates, a data search was carried out using keyword parameters which included "Anies Baswedan", "Ganjar Pranowo", and "Prabowo Subianto". Each candidate is taken data with a total of 1000 data. For this comparison in Figure 2.

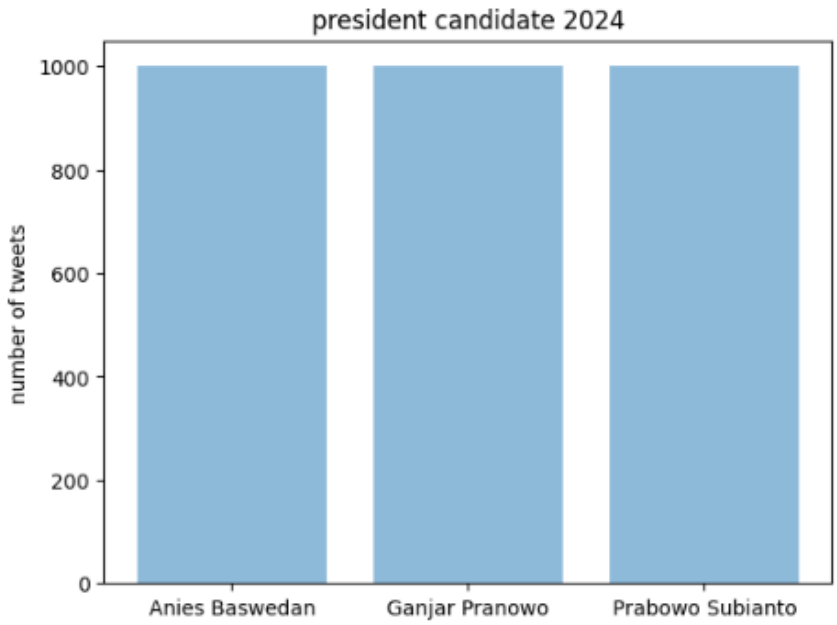


**Figure 2.** Data Chart

## 2. Import Data

After successfully collecting the dataset through the extraction process from tweets, the next step is to integrate the data into the planned analysis environment. The stages of importing and processing data are carried out through a processing platform from Google Colab, which is based on Python (Amani et al., 2020). Within Google Colab, data will be prepared for the pre-processing and development stages of a sentiment analysis model using the backpropagation-based SVM method. This integrated data set will form the basis for a more comprehensive public sentiment analysis in assessing the popularity and public perception of the three presidential candidates currently competing in the 2024 Presidential Election.

## 3. Preprocessing Data

Data preprocessing is done to normalize the tweet data to be processed and before the algorithm is implemented. Data preprocessing includes steps such as removing links, punctuation, and irrelevant words (Li & Chen, 2017). In addition, text data will be converted into a numeric representation that can be processed by the SVM model. The first preprocessing is to convert all words into lowercase letters. This is so that the machine can read the words more consistently and facilitate further text processing. In other words, converting the text to lowercase makes the text more uniform and helps in the understanding and analysis of the text by the machine.

The second preprocessing is to remove the text inside square brackets. This is done to remove information or text contained within square brackets, such as tags or annotations that may not be needed in text analysis or further processing. This is useful to focus on the core text and remove additional irrelevant elements. The third preprocessing is to remove links or URLs from the text. The aim is to remove any links that may be present in the text, as they often have no relevant text information and will only affect the text analysis or processing that is to be performed.

The next preprocessing is to remove punctuation from the text. Punctuation removal can help keep the text clean and focus on the words and sentence structure. Punctuation includes characters such as commas, periods, question marks, exclamation marks, and so on. The last preprocessing is removing certain words from the text. Word removal can be done to remove words that are considered irrelevant or noise in text analysis, such as common words that may not provide valuable information.

## 4. Support Vector Machine (SVM)

The Data Analysis technique known as SVM is an excellent method for categorizing data into various classifications (Wang et al., 2015). SVM maximizes the distance between data points of different classes by using a hyperplane as a dividing line. In the context of sentiment analysis, SVM can classify text based on the sentiments contained in it, such as positive, negative, or neutral (Shofiya & Abidi, 2021). There are 3 processes applied to the SVM classification process such as:

a. Linear SVM Optimization Function Objective
   SVM looks for a hyperplane (line or plane) that maximizes the margin between negative and positive classes. If x represents a feature vector and w is a weight vector, the formula for calculating the distance from point c to the hyperplane is as follows:

$$\text{distance} = \frac{|w.x+b|}{||w||} \tag{1}$$

   Here b is the bias, and ||w|| is the length of the vector w.

b. Support Vector Machine Linear Objective Function
   SVM attempts to find the weight vector w and bias b that minimizes it with the formula:

$$\|w\|^2 \tag{2}$$

   By following constraints:

$$y_i\,(w.x_i + b) \geq 1 \tag{3}$$

   Where $y_i$ is the class label(+1 or -1), $x_i$ is the feature vector, and i is the training data index.

c. Linear SVM Decision Function
   The decision to predict the class is determined by the sign of the decision function, namely the formula:

$$f(x) = w.x + b \tag{4}$$

   If $f(x) \geq 0$ then the class prediction is +1, and if $f(x) < 0$ then the class prediction is -1.

## 5. Backprogation

Backpropagation is a method used in the training process of ANN models (Wanto et al., 2017). This approach enhances the model's parameters by utilizing the gradient of the error function to perform optimization. In this study, the backpropagation method will be applied to the SVM model to improve the adaptability and predictability of the model to complex and varied sentiment data (Siregar & Wanto, 2017). In training this artificial neural network model applies several processes, namely:

a. Embedding Layer

The embedding layer changes the index of words in a vector representation that has dimensions. The mathematical functions performed by the embedding layer are:

$$E(x) = W.x \tag{5}$$

Where *E(x)* is the vector representation of the word x, W is the weighting matrix initiated during training, and x is the word index.

b. LSTM Layer

LSTM layers are a type of recursive layer in neural networks which are excellent for processing sequential data such as text (Zhou et al., 2015). The LSTM is equipped with an internal unit that helps overcome the issue of eroded gradients and allows the model to store data over a longer period (Chandar et al., 2019). The mathematical function performed by the LSTM layer is more complex and involves many parameters in the LSTM cells. In general, the operation of LSTM can be summarized as follows:

$$\begin{aligned} f_t &= \sigma(W_f \,.\, [h_t - 1, x_t] + b_f) \\ i_t &= \sigma(W_i \,.\, [h_t - 1, x_t] + b_i) \\ o_t &= \sigma(W_o \,.\, [h_t - 1, x_t] + b_o) \\ c_t &= f_t . c_{t-1} + \tanh\,(W_c . [h_{t-1}, x_t] + b_c) \\ h_t &= o_t . tanh(c_t) \end{aligned} \tag{6}$$

Where $x_t$ is the input at the t timestep, $h_{t-1}$ is the output at the previous timestep. $f_t$, $i_t$, and $o_t$ are gates that control the flow of information. $c_t$ is the cell state and $h_t$ is the output at timestep t. Parameters W and b are the weights and biases learned during training.

c. Dense Layer

Perform matrix addition operations and activation functions on the resulting previous output layer called the dense layer or the hidden layer. There are two dense layers. The mathematical functions performed by the dense layer are:

$$y = \sigma(W.x + b) \tag{7}$$

Where y is the output, W is the weight matrix, x is the input, and b is the bias. The activation function σ is non-linear like ReLu (Rectified Linear Unit) or softmax.

d. Softmax Activation

To create the distribution of each class, the softmax activation function is used, and the following is the formula used to implement this activation function:

$$P(y_i|x) = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \tag{8}$$

Where $P(y_i|x)$ is the prediction probability of class $e_i$ based on input x, e is an exponential number (2.71828), $z_i$ is the output from the previous layer connected to class $y_i$ and K is the number of classes.

## C. RESULT AND DISCUSSION

The implementation of sentiment analysis on tweets related to the 2024 Indonesian presidential candidates, with data collection from 1 to 30 July 2023, has been successfully carried out using the Support Vector Machine (SVM) method which integrates Backpropagation. This data has been processed and analyzed through the preprocessing stage and the SVM model training process by applying the backpropagation method.

### 1. Result Support Vector Machine

From the SVM model training process using the machine, evaluation values are obtained which include f1 score, recall, and precision. This evaluation provides an overview of the model's performance in classifying sentiment into positive, negative, and neutral categories. Data that has been preprocessed will be evaluated by the Support Vector Machine which is obtained using the Python programming language. This implementation includes importing the libraries used, converting text into TF-IDF, dividing training data and test data, creating SVM models and predictions from the given model. For point Y in the programming language below, the variable name will be changed according to the name of the variable to be evaluated. Anies_tweet for Anies Baswedan, Ganjar_tweet for Ganjar Pranowo, and prabowo_tweet for Prabowo Subianto, as shown in Figure 3.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import classification_report

vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(anies_Tweets['ClearTweet'])
y = anies_Tweets['analysis']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=42)

svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)

y_pred = svm_model.predict(X_test)
print(classification_report(y_test, y_pred))
```

**Figure 3.** SVM implementation Program Code

SVM classification results can be seen in the 3 tables of presidential candidates below:

a. Anies Baswedan

Anies Baswedan's SVM results, as shown in Table 1.

**Table 1.** Result SVM Anies Baswedan

| | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Positive | 0.00 | 00.00 | 0.00 |
| Negative | 0.00 | 0.00 | 0.00 |
| Neutral | 0.96 | 1.00 | 0.98 |

In the sentiment analysis of presidential candidate Anies Baswedan, the SVM model has low precision for positive and negative sentiments, as well as a higher recall rate, especially in identifying neutral sentiments. This indicates that the model tends to classify sentiment as neutral, but has difficulty recognizing positive and negative sentiments related to Anies Baswedan.

b. Ganjar Pranowo

Ganjar Pranowo's SVM results, as shown in Table 2.

**Table 2.** Result SVM Ganjar Pranowo

| | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Positive | 1.00 | 0.79 | 0.88 |
| Negative | 1.00 | 1.00 | 1.00 |
| Neutral | 0.98 | 1.00 | 0.88 |

For presidential candidate Ganjar Pranowo, the SVM model shows good performance in recognizing positive and negative sentiments, with high precision and recall values. In classifying neutral sentiment, the model has lower precision, but high recall, indicating the ability to recognize neutral sentiment well.

c. Prabowo Subianto

Prabowo Subianto's SVM results, as shown in Table 3.

**Table 3.** Result SVM Prabowo Subianto

| | **Precision** | **Recall** | **F1-score** |
|---|---|---|---|
| Positive | 1.00 | 0.88 | 0.93 |
| Negative | 0.00 | 0.00 | 0.00 |
| Neutral | 0.99 | 1.00 | 1.00 |

For presidential candidate Prabowo Subianto, the results of a neutral and positive sentiment model were identified which were quite accurate using SVM. However, the model's low precision and recall values in identifying negative feelings against Prabowo Subianto show that it frequently struggles to identify such sentiments.

In previous research, there was no word cloud so the target did not know the sentiment words that were widely discussed. The results of the 3 tables above illustrate how well the SVM model classifies public sentiment towards the three presidential candidates. In this analysis,

the model's performance in identifying positive, negative and neutral sentiments is considered, and it is measured by the relevant evaluation metrics.

## 2. Result Backprogation

After the SVM model has been properly generated, the backpropagation method must be used. The ability of the sentiment analysis model to identify and categorize public sentiment toward the three presidential candidates has significantly increased as a result of the backpropagation method's incorporation. From the evaluation results on the tweet data related to Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto, it can be found in Figure 4.

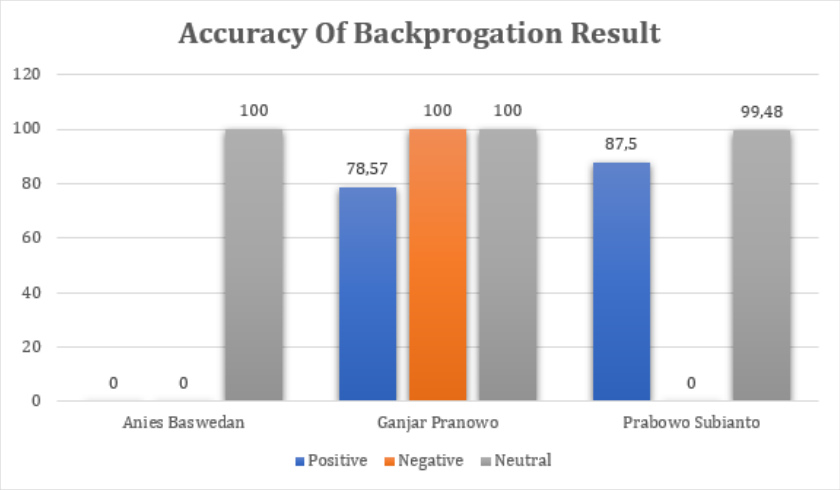


**Figure 4.** Comparison of Backprogration Accuracy

The picture above is a concrete result of applying the backpropagation method to a sentiment analysis model using SVM. For each of the three Indonesian presidential candidates 2024 the percentage values in the favorable, negative and neutral. These values reflect the extent to which the model has succeeded in classifying public sentiments related to each presidential candidate after the application of the backpropagation method.

a. Anies Baswedan
   Presidential candidate Anies Baswedan, the model has identified neutral sentiment in most of the data tweets associated with him. Even though the positive and negative sentiment values are 0%, improving the model's ability to recognize neutral sentiments has become the main focus of implementing backpropagation at this stage of the analysis.
b. Ganjar Pranowo
   The results of the Presidential Candidate Ganjar Pranowo, show a significant increase in the recognition model of negative and positive sentiments. Positive sentiment has a percentage of 78.57%, while negative sentiment has a percentage of 100%, indicating better performance after the backpropagation method is applied. In addition, neutral sentiment is also identified with a percentage of 100%, indicating the ability of the model to accurately classify neutral sentiment.

c. Prabowo Subianto

In the sentiment analysis of presidential candidate Prabowo Subianto, the results show an increase in the model's ability to identify positive and neutral sentiments. Positive sentiment has a percentage of 87.5%, while negative sentiment has a percentage of 0%. Neutral sentiment was identified with a percentage of 99.48%, which means that the high accuracy classification is in the positive and negative models.

Thus, this table provides a direct description of the extent to which the backpropagation method has improved the model's performance in classifying public sentiment towards the three presidential candidates. This improvement shows the potential of this method in increasing the accuracy and precision in the analysis of political sentiment through the backpropagation-based SVM approach.

## 3. Result Word Cloud

In addition to the evaluation results previously described, we also analyzed the words that appear most often in the tweet data regarding the three presidential candidates. We use the word cloud method to visualize the most dominant words in public conversations regarding Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto during the period 1 July 2023 to 30 July 2023. The word cloud provides an intuitive overview of the words most commonly used and can provide additional insight into the dominant sentiments associated with each presidential candidate.

a. Anies Baswedan

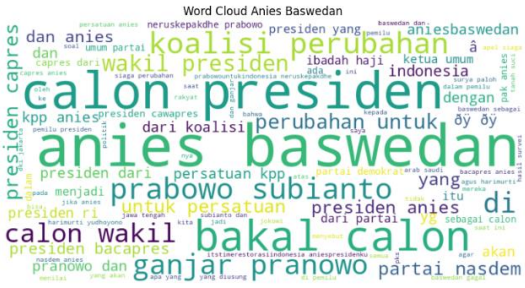


**Figure 5.** Word Cloud Anies Baswedan

b. Ganjar Pranowo

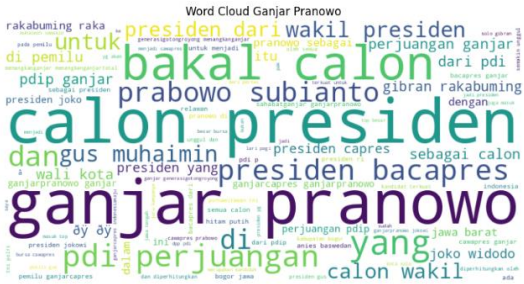


**Figure 6.** Word Cloud Ganjar Pranowo

c. Prabowo Subianto


**Figure 7.** Word Cloud Prabowo Subianto

Using this word cloud visualization, we can easily identify the words that are often associated with each presidential candidate and gain deeper insight into the main sentiment patterns in public discussion about them.

## D. CONCLUSION AND SUGGESTIONS

In this study, the backpropagation-based (SVM) technique has been successfully applied to the sentiment analysis of tweet data pertaining to three presidential candidates: Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto. Evaluation findings on the model's performance in categorizing positive, negative, and neutral attitudes have been achieved through the data pre-processing stage, the SVM model training procedure, as well as the application of the backpropagation approach.

The evaluation shows that the backpropagation-based SVM method has significantly improved the model's ability to classify public sentiment towards the three presidential candidates. This model has demonstrated better adaptability in recognizing neutral, negative and positive sentiments, with superior results after the application of the backpropagation method. This performance improvement is clearly illustrated in the comparison results obtained from the application of backpropagation-based models, which have been able to provide better accuracy. Further research can be carried out using this backpropagation-based model to observe the broader response of the public towards presidential candidates in various contexts, such as public debates, campaign policies or other important events. In addition, more in-depth exploration regarding the use of special features in the data pre-processing stage and modification of the backpropagation method can be a direction for further research to improve the weaknesses identified in the sentiment analysis of negative sentiment regarding Prabowo Subianto. Overall, this research makes a significant contribution to understanding public views of presidential candidates and provides an important foundation for further development in the analysis of political sentiment.

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