The Role of Sentiment Analysis in Election Predictions Compared to Electability Surveys

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ABSTRACT (10 PT)

Indonesia has just held the voting process for the Presidential Election. This has become a discussion of various media to social media, especially Twitter. However, when making predictions based on social media it will be so difficult if there is no specific technique or method for handling it. The prediction method we found in Indonesia often uses electability surveys in elections, but this research will compare it with sentiment analysis that utilizes social media in data collection. Another novelty is the data used during candidate campaign debates using the Support Vector Machine (SVM) method in class classification. The results obtained show that there are still differences between electability and sentiment, but this is due to several factors such as the amount of data, data objects, data collection time span, and methods. Overall, the SVM method has an accuracy of more than 0.75 on all three candidate datasets, proving that this method can be applied to similar cases.

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1. INTRODUCTION

The presidential election is one of the election processes in Indonesia at the national level. Indonesia has just completed this process, and candidates have been preparing for it for a long time before voting day. Candidates in the election cannot be distinguished between the eligibility factor and the electability factor [1]. Eligibility refers to whether a person is qualified or can perform duties related to the position for which they are applying. While electability refers to how popular or likely a candidate is to win in a general election. Notability factors such as partisanship, which means certain endorsements or preferences of certain parties as well as other factors such as their political track record, qualifications, character, or even public image. Many political parties analyze their candidates by considering the aforementioned factors to win the election contest.

In recent years, social media has experienced rapid growth, becoming the primary platform for the global dissemination of information [2][3]. Social media has a great influence on its use [4], providing ample opportunities for politicians to reach audiences directly at minimal cost [5]. This provides an opportunity for campaign teams and political parties in the coalition to campaign more efficiently through social media, reaching voters faster. One social media that is widely used to discuss Election messages is Twitter (X) which is becoming a popular social media platform because it allows users to send short messages, pictures, and videos [6]. Through Twitter (X), users can express their opinions [7]. The use of Twitter (X) also has many users in Indonesia and is certainly utilized as campaign media. Through people's opinions or views on candidates who appear in the election, the potential of social media in dealing with election issues becomes more complex to discuss.

Sentiment analysis comes as problem solving in terms of analysis of large amounts of data. One of the difficulties experienced in predicting election results is the traditional way of obtaining, processing and providing recommendations from the results of the data obtained. Sentiment analysis is a solution to the problem. Sentiment analysis is a research field those studies statements, attitudes, and emotions [8]. The presence of this approach is one of the solutions that can be used by policy makers in determining the development pattern of community partisanship in elections in an updated manner.

Based on this, this study will discuss sentiment analysis in predicting election results rather than electability. The novelty in this study compared to previous studies is that this study will be linked to electability and the timing of data collection using data during the candidate's campaign. The underlying problem is that electability and sentiment analysis are different but have the same purpose in this case. Although with different methods between the two, this research is more about the method used in Sentiment Analysis, namely Support Vector Machine (SVM) because this method is superior in the case of sentiment analysis [9], as in some studies [10][11]. The data used comes from the social media platform Twitter (X) taken during the candidate's campaign period. This research is important to discuss because the impact of comparison between sentiment analysis-based methods with electability that have the same usefulness can be compared to be an offer to be applied in the case of elections.

2. RELATED WORK

Many studies have applied sentiment analysis approaches based on Twitter data [12][13][14][15][16]. Other research on political discussions has also been carried out such as post-election analysis to prediction of results (before the election) conducted during the campaign period. For example, in research [17] the posts of politicians from the Greek, Spanish, and British Parliamentarians were systematically analyzed. The post is determined based on its content or negative sentiment so that it spreads/goes viral faster than other ordinary posts. Another study [18] utilized computational methods, coding, and statistical analysis on more than 300,000 tweets during the 2020 US Presidential election. The data is categorized by gender to get the topics discussed during the Election. Another study [8] also used Facebook comment data on the 2019 Indonesian presidential election to gain the popularity and sentiment of presidential election candidates. The percentage of popularity of the Jokowi-Ma'ruf pair was 40.52% and the Prabowo-Sandi pair was 59.48%. The percentage of positive sentiment obtained by the Jokowi-Ma'ruf pair was 56.76 and negative sentiment was 43.24%. While the Prabowo-Sandi pair has a percentage of positive sentiment of as much as 24.21% and negative sentiment of as much as 75.79%.

Recent research [19] on sentiment analysis was used to analyze public opinion on his alignment with the Presidential candidate in the 2023 Nigerian Presidential Election. The alignment of the community was analyzed based on the sentiment obtained from Twitter data with negative, neutral, and positive class categories. Like the research topic, another study [20] analyzed public sentiment toward candidates for the 2023 Nigerian Presidential Election using LSTM, Linear SVC, and BERT methods.

The results of the General Election prediction based on sentiment analysis used using Twitter data for the period January to March 2019 in India correspond to the actual election results available [21]. Other research [22] also suggests the chances of predicting the outcome of the Presidential Election based on a social media framework using Machine Learning. The data comes from social media Twitter, Facebook, and Instagram is more than 65,000 posts. A total of 195 polls for presidential predictions in Argentina (2019), Brazil (2018), Colombia (2018), and Mexico (2018). The results showed that there was a high degree of accuracy in predicting the results of the vote for various candidates as well as providing daily predictions. This is better than traditional polls and can be applied using predictions of upcoming elections to similar scenarios. A similar scenario in another study [23] suggested that social media data can predict election outcomes. Analyze the correlation between social media performance (Facebook, Twitter, and Instagram) with the votes obtained in the election. More than 40,000 posts from January to October 2018 in Brazil have been able to provide a strong correlation between the proposed model and the actual votes obtained.

3. METHODS

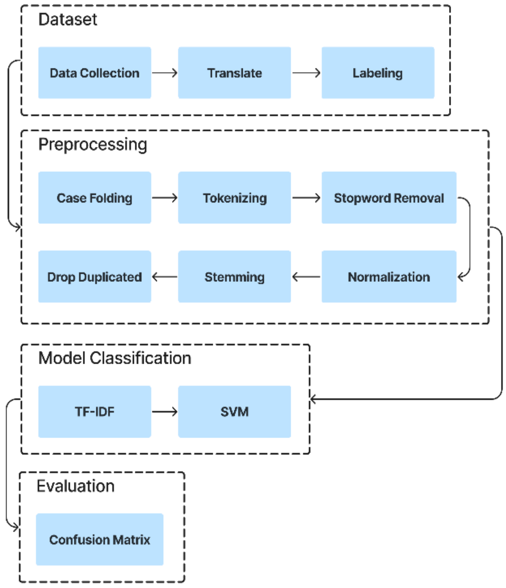

Fig. 1. Overview of Sentiment Analysis

Figure 1 shows the sentiment analysis flow from data collection to evaluation for a classification model.

3.1. Dataset and Labelling

The dataset used is a dataset accessed during the Indonesian Presidential Election candidate debate on the Twitter platform using the Twitter API. The debates were held five times, and we accessed data on all five debates. The number of data obtained by each Presidential Candidate, namely Anies Baswedan as many as 3,385 data, Prabowo Subianto as many as 3,359, and Ganjar Pranowo as many as 2,383. The labeling technique used to determine sentiment on the analyzed data is VADER. VADER makes use of a combined lexicon of sentiment and a collection of lexical features, such as words, which are typically classified by their semantic direction as positive or negative [24].

3.2. Preprocessing

Information is processed through a pre-processing stage to clean up the data, including steps such as case folding, tokenizing, stop word removal, normalization, stemming, and finally, duplicate elimination to reduce identical tweets (spam) and empty tweets [25].

3.3. TF-IDF

A method known as reverse document frequency (also called TF-IDF) is an effective way to assess the significance of words in a document. The frequency of a word (t) is calculated as the number of occurrences of it in the document divided by the total words in the document. IDF (Inverse Document Frequency) is used to determine the level of significance of a word [26].

3.4. Classification

A well-known supervisory classification method, Support Vector Machine (SVM) has been widely applied in various fields. The essence of nonlinear SVM classification training is to solve convex Quadratic Programming (QP) problems, in which the execution time is strongly influenced by the interaction of quadratic terms with the optimizer used [27]. This method is superior to other methods in terms of classification [11][10], especially in the case of sentiment analysis [9]. Support Vector Machine works by finding the best separator field and maximum margin to separate the data [28]. The Support Vector Machine equation can be seen in (1) [29].

$$w - x.b = 0 \quad (1)$$

In this context, w represents a weight vector, x represents an input vector, and b represents bias.

3.5. Evaluation

Scoring methods for classification include precision, accuracy, recall, and F1 scores, which have proven useful in confusion matrices [30], shown in the following formula (2), (3), (4), (5).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+FN+TN)} \quad (2)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (3)$$

$$Recall = \frac{TP}{TP} + FN \quad (4)$$

$$F1 = 2\, x\, precision\, x\, \frac{recall}{precision} + recall \quad (5)$$

True Positive (TP) indicates that the previous model successfully predicted correctly. True Negative (TN) describes a situation where the previous model was wrong in its predictions. False Positive (FP) signifies that the previous model incorrectly predicted something that didn't happen. A False Negative (FN) indicates that the previous model failed to predict an event that occurred [31][32][33].

4. RESULTS AND DISCUSSION

4.1. Sentiment VS Electability

Although most candidates in the election in Indonesia use electability surveys to find out their vote predictions in the election, the possibility of candidates choosing sentiment surveys as an option in the future will also be open. This study only reviews some theories obtained in the field related to electability and compares them with candidate sentiment. Some of the differences used as a comparison between the two surveys are as shown in Table 1.

TABLE I. DIFFERENCES IN ELECTABILITY AND SENTIMENT

Scope	**Difference**	
	Electability	***Sentiment***
Goals	Measure public support for candidates	Measure public views, opinions, or feelings toward candidates
Method	Structured questionnaire	Questionnaire surveys, social media analysis, text analysis, and data analysis techniques
Context	Understand the relative position of competing candidates in elections, as well as to predict the outcome of elections	To understand public support for political figures
Data	Tends to be small due to voters' preference for certain political candidates in certain elections	Tends to be larger than data from electability surveys
Budget	Tends to require a significant budget	Tends to be smaller budget used than electability surveys

Table 1 shows the difference between electability and sentiment. There are five factors as a comparison, namely goals, methods, context, data, and budget

4.2. Results

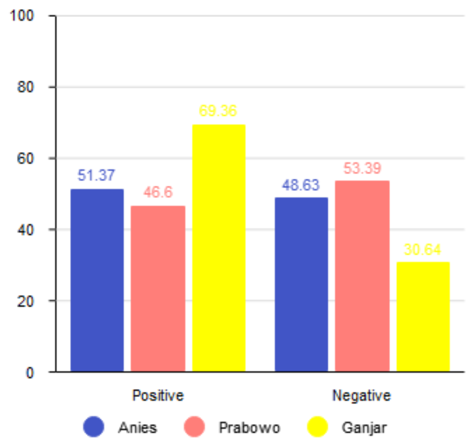

Fig. 2. Labeling Class Positive and Negative of Candidate

The data obtained on each presidential candidate was obtained with different amounts. The process of translating documents into English is carried out because it uses the VADER library in determining the sentiment class to positive or negative as shown in Figure 2.

Figure 2 shows the positive and negative class labeling on all three Presidential candidates. In percentage terms, the most positive cases were obtained in a row in Ganjar Pranowo at 69.36%, Anies Baswedan at 51.37%, and Prabowo Subianto at 46.6%. While the most negative in a row were Prabowo Subianto at 53.39%, Anies Baswedan at 48.63%, and Ganjar Pranowo at 30.64%.

After the process, the document goes through preprocessing stages such as case folding, tokenizing, stopword removal, normalization, stemming, to drop duplicated. However, after going through the preprocessing stage to the duplicated drop stage, the number of data obtained for each presidential candidate, namely Anies Baswedan as many as 2780 data, Prabowo Subianto as many as 2755 data, and Ganjar Pranowo as much as 1103 data.

4.3. Classification and Evaluation

Based on the results obtained, the SVM used at the testing stage is Linear SVM. SVM performs a linear classifier of the maximum interval specified in the feature space [34] using three C parameters, namely C= 0.1, C=1, and C=10.

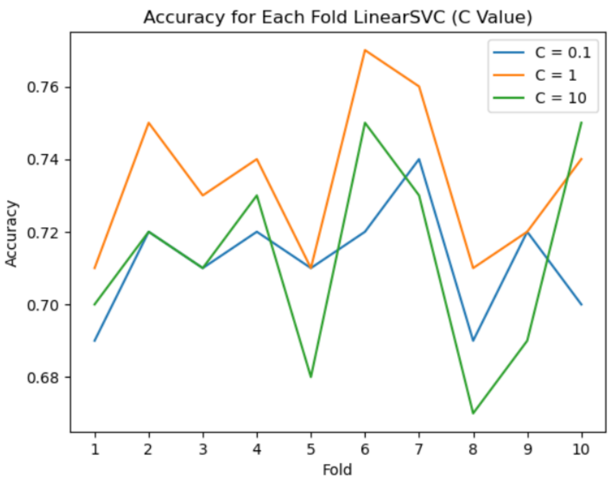

Fig. 3. Accuracy for Anies Baswedan

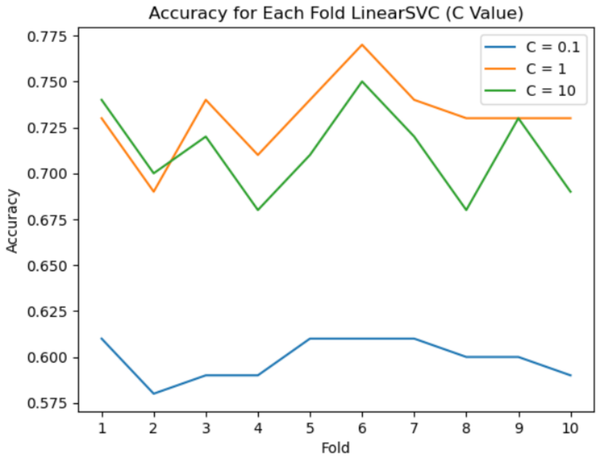

Fig. 4. Accuracy for Prabowo Subianto

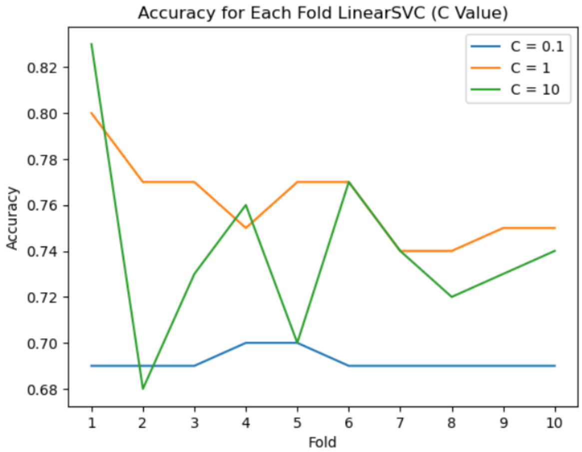

Fig. 5. Accuracy for Ganjar Pranowo

Figure 3, Figure 4, and Figure 5 respectively show the linear accuracy of SVC on three C parameters for Anies Baswedan, Prabowo Subianto, and Ganjar Pranowo. Based on the results of the three candidates, the best accuracy is shown in the Ganjar Pranowo dataset, which is 0.83 on the C=10 parameter. As for the dataset of Anies Baswedan and Prabowo Subianto, accuracy was obtained by 0.77 on the C = 1 parameter.

5. DISCUSSION

A fundamental tool to measure the level of victory of candidates in elections is the electability survey. However, sentiment analysis comes with a feature of public sentiment towards the figures nominated in the election. This makes a new color in election prediction through social media compared to electability surveys. The problem in categorizing people's posts through social media towards a candidate in the election can be answered by the presence of sentiment analysis. We get this as a comparison for policy makers in utilizing this approach compared to electability surveys.

Electability and sentiment surveys have the same purpose in terms of elections for the prediction of candidate results. Electability measures public support for a candidate while sentiment measures a user's opinions, views, and feelings toward a candidate. The application of electability is a survey that is widely used for now, but it does not rule out the possibility that sentiment will be widely used in election discussions. There are five indicators that become a comparison such as goals, methods, context, data, and budget that will be considered in using electability and sentiment survey techniques.

In terms of the results obtained, this time we found differences between the results of these two prediction approach methods. However, this is due to several factors such as the time of data collection, the amount of data, data objects that only take data on presidential candidates, and the influence of other things. One of the other fundamental things that results in the acquisition of the collected data is the privacy of user data that must follow the policies of the platform used. This has an impact on the amount of data that can be processed as material for analysis in this study. The results of the Populi Center survey showed Prabowo-Gibran's electability was the most superior at 52.5%, followed by the Anies Baswedan-Muhaimin and Ganjar-Mahfud pairs of 22.1% and 16.9% respectively conducted from January 27 to February 3 on 1,500 respondents from 38 randomly selected provinces. Meanwhile, the results of the Charta Politika survey for the period January 4-11, 2024, showed Prabowo-Gibran's electability fell to 42.2%, while Anies-Muhaimin and Ganjar-Mahfud were at 26.7% and 28%, respectively. Another Political Indicator survey in the period 10-16 January 2024 showed the electability of the Prabowo-Gibran pair at 48.55%, Anies-Muhaimin 24.17%, and Ganjar-Mahfud 21.6%. While the order of sentiment results obtained in this study based on the percentage of positive sentiment is Ganjar Pranowo which is 69.36%, Anies Baswedan which is 51.37%, and Prabowo Subianto which is 46.67%.

In terms of accuracy, the best dataset is obtained on the Ganjar Pranowo dataset in the C=10 parameter. One of the things that affects it is the amount of data that differs between the three candidates after preprocessing because the Ganjar Pranowo dataset is smaller than other candidate datasets. Overall, all three datasets have an accuracy of over 0.75, which suggests that this linear SVM method can be used in other similar cases. Another factor that led to the different results was the inability to handle the imbalance between the two positive and negative labels.

6. CONCLUSION

This research found that electability and sentiment surveys have the same goal of being able to predict election results. However, with some differences in the amount of data, objects, and methods used, resulting in differences obtained in this case. The sentiment method used is linear SVM with three parameters C, namely 0.1, 1, and 10. Based on the three presidential candidate datasets, Ganjar Pranowo has the most positive results and the highest method accuracy of 0.83 at parameter C = 10. One of the reasons for this is because the data tends to be smaller than the data of the other two candidates. Overall, all three datasets have an accuracy above 0.75 and this proves the method can be applied to other similar cases. Although with different calculation methods, electability and sentiment have their own advantages and disadvantages in handling this case.

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