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Twitter Sentiment Analysis Towards Candidates of the 2024 Indonesian Presidential Election

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Abstract

Indonesia will hold general elections in 2024. Long before the elections were held, the topic related to elections was widely discussed on news portals and social media, including Twitter. A few studies related to Indonesian election have tried to predict candidates who will run for the presidential election, but there has been no research that examines public sentiment on social media towards each of the potential candidates. The main objective of this study is to analyze the public sentiment in Twitter towards potential candidates for the 2024 Indonesian presidential election. This research seeks to fill the gaps in previous research and become a reference for further research regarding the sentiment analysis for election prediction using Twitter. The presidential candidates used in the research are the top 3 candidates based on the Poltracking survey, namely Ganjar Pranowo, Prabowo Subianto, and Anies Baswedan. The data were taken from January until October 2022, more than a year before the general election began. To predict the sentiment, four different machine-learning methods were used and compared to each other. There are Naïve Bayes, Support Vector Machine, Random Forest, and Neural Networks. The result shows that the number of tweets discussing each candidate from January until October 2022 has increased over time for each month. Based on the sentiment results of each candidate, the highest sentiment towards Prabowo is neutral (55.49%), the highest sentiment towards Ganjar is positive (61.34%), and the highest sentiment towards Anies is neutral (44.84%). Result from the study also shows that Anies was the presidential candidate who received more negative sentiment than the other two (56.63%). Meanwhile, Ganjar Pranowo got the most positive sentiment of all (42,69%). For the neutral sentiment, Anies Baswedan also got the most results (39,87%), followed by Prabowo (38.99%) and Ganjar Pranowo (21.14%). Result of the study also discovers that Random Forest and Neural Networks have the best performance for sentiment analysis. Other than that, experiment from this research also discovered that using a model for each entity can generate sentiment results specific to the candidate being analyzed, rather than sentiment for the tweet as a whole. This show that a model for each entity can give better results than using an aggregated model to determine the sentiment of each candidate.

Keywords: *twitter; sentiment analysis; presidential election*

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1. Introduction

Indonesia will hold general elections in 2024. Long before the elections were held, the topic of elections was widely discussed on news portals and social media. Even before the general election commission (KPU) officially determines the candidates for the 2024 general election, there are many names who are being rumored and discussed to be running in the election. Based on a survey conducted by the Poltracking survey institute in October 2021, the names of candidates who have the potential to run in the general election includes Ganjar Pranowo (22.9%), Prabowo Subianto (20%), Anies Baswedan (13.5%), Ridwan Kamil (4.1%), Agus Harimurti Yudhoyono (3.3%), Sandiaga Uno (2.8%), Khofifah Indar Parawansa (2.5%), Puan Maharani (1.9%), Gatot Nurmantyo (1.2%), Andika Perkasa (1.2%), Airlangga Hartanto (1%), Erick Tohir (0.9%), Mahfud MD (0.8%), Muhaimimin Iskandar (0.3%), and Zulkifli Hasan (0.2%) [1].

Topics related to presidential candidates are also widely discussed on social media, including Twitter. Twitter is often used in research related to analyzing public sentiment towards candidates and predicting the election results [2] - [6]. Twitter is also one of the social

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media that is widely used by Indonesian people to express their personal opinions. Ahead of the general election which will be held in 2024, netizens have begun to tweet a lot of their opinions regarding several names who will be proposed as presidential candidates.

As one of the largest social networks, Twitter provides a concise platform for people to express opinions and share views on various topics and issues [7]. Twitter has unique characteristics that other platforms don't have. Every tweet shared in Twitter can be read by anyone connected to the internet unless the user profile is set as private. Twitter also allows users to quickly share information and interact with other user who may not connected to their network through specific topics by using hashtags [8].

To analyze opinions in tweets, sentiment analysis can be applied as an approach that uses Natural Language Processing (NLP) to extract, convert, and interpret opinions from a text and classify them into positive, negative, or neutral sentiments [9]. Several studies related to sentiment analysis using Twitter show promising results when compared to the polling data or actual election results. Research from Rodriguez et.al [10] which aim predict the outcome of the Chilean election, has the results that were close to the real percentage and the prediction of who will win the election was correct. Study conducted by Budiharto and Meiliana regarding sentiment analysis also proved a good results in predicting and analysing the Indonesian presidential election using Twitter data [11]. Furthermore, research conducted by Bansal and Srivastava [12] also showed a good results on predicting elections result in India using Twitter data.

Different techniques have been used in conducting sentiment analysis in Twitter towards the presidential candidates or predicting the election results. However, machine learning and data mining, which are subfields of computer science, are among the most widely applied techniques in research related to predicting election results from Twitter data. Rodriguez et.al [10] compare four supervised machine learning algorithms in conducting sentiment analysis to predict election results in Chile. Those machine learning methods are Decision Trees, Random Forest, AdaBoost, and Linear Support Vector Machine. Study by Singh et.al [13] also used information from Twitter related to the 2017 Punjab assembly elections. The researchers applied various social media analysis, machine learning methods, and network analysis to extract and discover hidden but useful information. There is also research from Singh [14] which tries to compare four methods from machine learning and deep learning domain to predict USA presidential election result.

Related to the 204 Indonesian presidential elections, there are several studies being conducted to predict the potential candidates for presidential election. Study conducted by Masud et.al forecast the political parties and candidates running for president of Indonesia in 2024 using Nvivo 12 software for descriptive content analysis and Twitter users for research subjects [2]. The information was collected from Twitter using keyword "Pilpres 2024." According to the research results, three names emerged that have the most chances to become presidential candidates, namely Anies Baswedan, Prabowo, and Ganjar Pranowo. Study conducted by Baharuddin et.al also use Twitter analysis to predict and forecast candidates for the Indonesian presidential election in 2024 [15]. The study used Twitter search focusing only on official accounts for the potential candidates. There are 8 candiate accounts being used for the study, @ganjarpranowo, @prabowo, @aniesbaswedan, @ridwankamil, @agusyudhoyono, @sandiuno, @khofifahip, and @puanmaharani_ri. The study succeeded in mapping out three potential candidates in the 2024 election, Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto.

However, existing research related to the 2024 Indonesia presidential election has not presented in detail the public sentiment towards each presidential candidate and the development of public sentiment on Twitter over time. Existing research also did not specifically use candidate names as search keywords.

The main objective of this study is to analyze the public sentiment in Twitter towards potential candidates for the 2024 Indonesian presidential election. This research seeks to fill the gaps in previous research and become a reference for further research regarding the sentiment analysis for election prediction using Twitter. The presidential candidates used in the research are the top 3 candidates based on the Poltracking survey, namely Ganjar Pranowo, Prabowo Subianto, and Anies Baswedan. The data used in this research was tweet data collected from January to October 2022, one year before the determination of the presidential candidates and the general election being held. The reason for choosing this data was because the presidential candidates had begun to be widely discussed in Twitter at that time. There are three questions that this research aims to answer:

RQ1: How is the Twitter sentiments towards the three candidates of the 2024 Indonesian presidential election?

RQ2: What is the best algorithm for analyzing the Twitter sentiment of Indonesia's 2024 presidential candidates?

RQ3: What is the best model for classifying tweets that mention more than one entity? Using a prediction model for each entity or aggregated model that classifies tweets as a whole?

The structure of this paper is as follows. Section 1 gives a brief background of this research and the objectives of the study. Section 2 discusses the literature review. The research method is discussed in Section 3, while the result and discussion are presented in Section 4. The conclusion of this study discusses in Section 5 by outlining the key points found. Finally, section 6 discusses the limitation and recommendations for future works.

2. Research Methods

This study aims to analyze public sentiment toward Indonesia's presidential election candidates in 2024 through social media text analysis. The data used in the study was obtained from Twitter. To create a predictive model, a random sample of tweets was selected from the entire data. The tweets of the dataset sample were read and classified by two people. The data then split into 70:30 for training and testing respectively. Then, machine learning models were built on this sample data set.

Performance evaluation was based on the calculation of accuracy, precision, recall, and f1 score. The results of the sentiment analysis were then visualized, and an in-depth analysis was carried out to answer the research questions. The research process can be seen in Figure 1. Each of the processes will be explained in more detail in the following subsections.

The top 3 candidates of 2024 Indonesian presidential election based on Poltracking survey were Ganjar Pranowo, Prabowo Subianto, and Anies Baswedan. Therefore, the data collection from Twitter API will be focused on the following keywords: *"anies"*, *"prabowo"* and *"ganjar pranowo"*.

The tweets were taken using Twitter API by the help of Snscrape library. Tweets were limited to Indonesian language only and have also been filtered out from content that is not useful for sentiment analysis such as links, URLs, username, retweets, and likes. Data collection was carried out from January until October 2022, with a total of 231.514 tweets obtained. After data being collected, the manual data labelling were conducted to obtained a labelled data set.

Manual labelling was carried out by 3 annotators. in the first stage, two annotators performed manual labeling independently. then, the third annotator is tasked with determining the final label if there is a difference of opinion between annotator 1 and annotator 2. When carrying out manual labelling, guidance is also provided so that the labelling is more focused and structured. The labelled data will later be used for sentiment analysis model construction and testing.

The purpose of preprocessing is to perform a filtration process to retrieve the most important and meaningful part of the data. The preprocessing was performed on labeled data, and it includes data cleaning, tokenization, normalization, stop words removal, and stemming. *Data Cleaning*: process to cleaning up irrelevant parts from the tweet such as links, media URLs, emoticons, etc. *Tokenization*: dividing the text into parts that are called tokens. Tokens can be formed in words, phrases, or other meaningful elements. *Normalization*: a process of canonicalizing tokens so that matches occur despite superficial differences in the character sequences of the tokens. Normalization includes the process of changing slang words or non-standard words into their standard form. *Stop words Removal*: a process of removing common and often used words that does not have a significant effect in sentences. 5. *Stemming*: a process of transforming token of word to the standard form called stem.

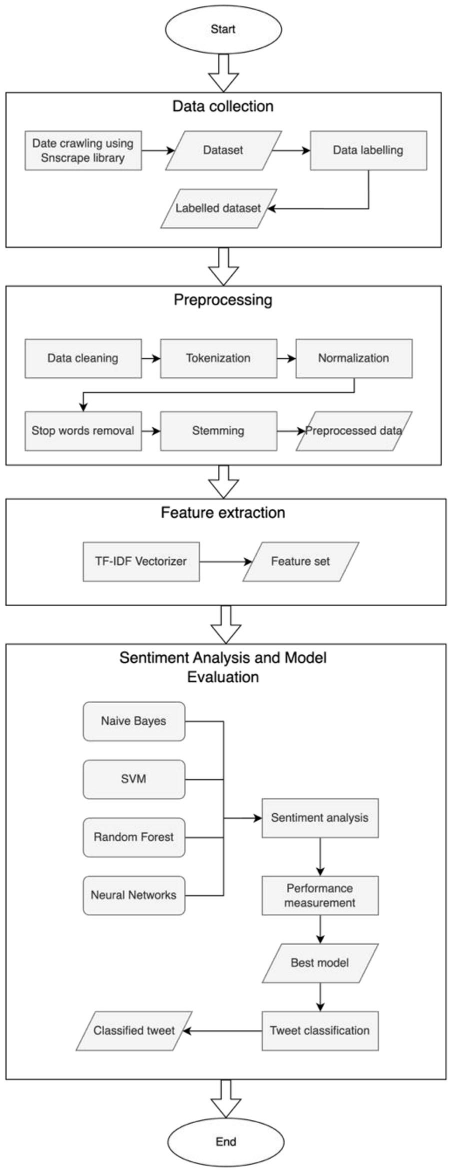

Figure 1. Research Methods

TF-IDF (Term Frequency – Inverse Document Frequency) is a well-known technique in Natural Language Processing (NLP) to derive useful words and their scores from a given corpus [16]. TF represents the number of specific words that appear in the corpus. Meanwhile, IDF describes the inverse of multiplication DF (document frequency) which describes how many documents contain certain terms. Along with TF, it gives a measure of the occurrence of certain words as shown in Formula 1.

$$tf - idf = tf \times log_{df}^{N} \quad (1)$$

Sentiment analysis, or opinion mining, is one of the popular subjects in natural language processing and computational linguistics to analyze text and infer sentiment. To predict the sentiment of Indonesia's presidential election candidates using Twitter data, four different machine learning methods were used and compared to each other. These methods are listed below.

Naïve Bayes is a well-known classification technique [17]. It uses Bayesian statistics which assumes that the features are statistically independent of each other. Due to this assumption, Naïve Bayes can learn high-dimensional data with minimal training. Naïve Bayes is a supervised machine learning method. Naive Bayes is also scalable and very lightweight. As the tweet data continues to grow over time, several studies addressed that this is the most suitable classifier for text analysis with stable and predictable results [17], [18].

SVM has a strong mathematical basis, and it also has one of the best performances when applied to text documents [10]. SVM is a linear classifier method that works by finding the optimal hyperplane that separates the classes given the training data. This hyperplane is obtained by solving an optimization problem, and the solution to this optimization problem leads to the concept of a support vector.

Random Forest (RF) is a decision tree-based ensemble model that can be used for regression and classification [19]. This method achieves highly accurate predictions by combining multiple poor learners (decision trees) from training data and random feature selection.

Neural Network is a classification algorithm that is composed of biologically inspired layers of nodes or neurons that constitute human brains. It consists of input, hidden, and output layers [20]. The hidden layers lie between the input and output layers. The input layer accepts input as features of training data. The output from the input layer is further fed into the hidden layers. The hidden layers process input and forward output to the output layer. The backpropagation method for Neural Networks repeatedly adjusts the weights of links in the network iteratively to minimize the error between actual output and desired output. In the sentiment analysis study, Neural Networks can be used by training features of Tweets along with their polarity labels. The number of input neurons will be the number of input features (varies for each dataset). The one hidden layer is used to conduct the experiments.

Entity sentiment analysis focuses on analyzing sentiments expressed in a document towards a particular entity [21]. Entity refers to a specific object such as a person, a party, an institution, etc. Entity sentiment analysis aims to calculate sentiments towards an individual entity in a document rather than obtaining a single sentiment score for the whole document. The key to accurately expressing sentiments about an entity is to identify what sentiment words directly relate to and contribute to that entity.

Moilanen and Pulman further proposed a fuse model by leveraging the sentiments with different boundary levels [22]. Each constituent was regarded as a sub-context of the target entity. The study demonstrated how compositional sentiment parsing lends itself naturally to multi-entity sentiment scoring with minimal modification. Results obtained from two scoring methods suggest that, despite the inherent complexity and subjectivity of the task, compositional sentiment parsing can generate sensible analyses that emulate human multi-entity sentiment judgments effectively.

Targeting the errors caused by multiple entities in the process of target entity sentiment analysis, another study by Luo and Mu proposed a smoothing algorithm and develop three NSSM (Negative Sentiment Smoothing Model) models to help improve entity sentiment assessment in the news context [21]. The study explored a case of three main media news reports on the 45th President of the United States to reveal the sentiments involved in this news. Using Euclidean distance evaluation, accuracy evaluation, and precision evaluation, the study showed that the developed NSSM models improved the performance of entity sentiment analysis.

Ding et al. conduct an entity-level sentiment analysis tool for issue comments in GitHub consisting of sentiment classification and entity recognition [23]. Their study aims to classify issue comments into three categories including negative, positive, and neutral ones, and recognize the entity of the subjective comments in the form of a <sentiment, entity> tuple for each issue comment, where the entity is either ‘Person’ or ‘Project’. Evaluation of the sentiment classification using ten-fold cross-validation showed that the mean precision, mean, recall and accuracy were significantly higher than existing tools like SentiStrength-SE and o SentiStrength.

3. Results and Discussions

The following section will describe the results of the data collection from Twitter, along with the comparison of four machine learning methods to predict sentiment of each candidate.

3.1 Twitter Data

Data collection from January until October 2022 obtained total of 231.514 tweets. The result shows that Anies Baswedan was the most discussed candidate on Twitter from the period (88.005 tweets), followed by Ganjar Pranowo (73.980 tweets) and Prabowo (69.529 tweets). The results also showed that the number of tweets for the three candidates has significantly increased every month. The percentage of total Tweets from each candidate and the distribution of tweets from January until October 2022 can be seen in Figure 2 and Figure 3.

After collecting the data, manual annotation was conducted to labelling 5000 tweet data of each candidate from the entire dataset. The 5000 manually annotated tweet data will later be used as a dataset for model constructions and testing. The manual annotation produces the distribution of data as shown in Table 1 and Figure 4.

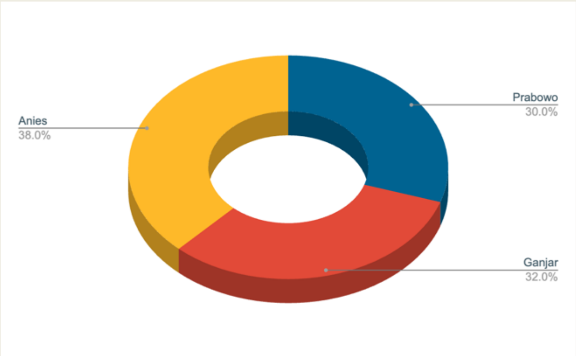

Figure 2. Percentage of total tweets from each candidate

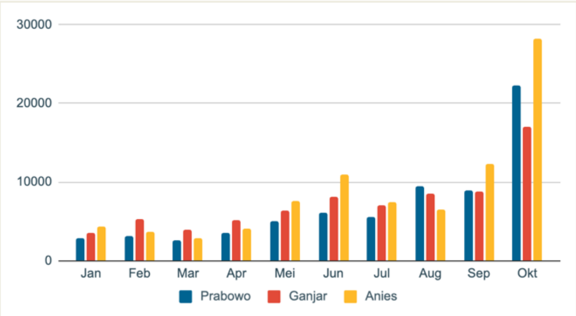

Figure 3. Distribution of tweets from January until October 2022 for each candidate

Table 1. Total tweets from each candidate

Candidate	Tweet	Percentage
Anies Baswedan	88.005	38.01%
Ganjar Pranowo	73.984	31.96%
Prabowo	69.529	30.03%
Total	231.514	100%

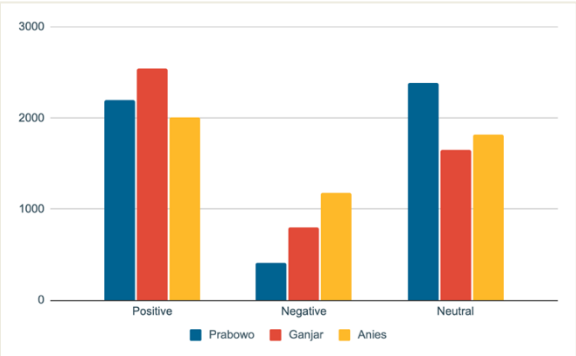

Figure 4. Distribution of class label from manual annotation

3.2 Model Comparison

Four machine learning methods were used to perform sentiment analysis. The classification models were made for each dataset of candidate using all four machine learning methods and then compared to find the best method. When performing the testing and evaluation, we also use k-fold cross-validation to evaluate the performance of the model by dividing the data samples randomly as training data and testing data and grouping the data as many as k from k-folds. In this study, we used 5-fold cross-validation.

To measure the model, apart from using accuracy, we also considered the calculation of precision, recall, and f1 score. Precision is the comparison between True Positive (TP) and the amount of data that is predicted to be positive. Recall is a comparison between True Positive (TP) and the amount of data that is actually positive. Meanwhile, f1 score is the harmonic mean from precision and recall. To choose the best model, we use the f1 score with the consideration that this value indicates that our classification model has good precision and recall.

From test results that have been carried out, the best model for Prabowo and Ganjar was obtained from the Random Forest model. Anies dataset obtained the best results from the Neural Networks model. Meanwhile, the model that combined all datasets from candidates has the best result from the Neural Networks. Detail of the results and the comparison for each algorithm can be seen in Table 2.

Table 2. Labelled data for each candidate

	Prabowo	Ganjar	Anies
Positive	2202	2545	2007
Negative	414	802	1174
Neutral	2384	1653	1819
Total	5000	5000	5000

After the best model of each candidate and the combination model were obtained, the four models were then used to perform sentiment analysis of the entire data that has been collected from January until October 2022. The model of each candidate was used to get sentiment results from each candidate dataset itself. In this case, the Prabowo model was used to get sentiment from the entire Prabowo dataset, the Anies model was used to get sentiment from the entire Anies dataset, and the Ganjar model was used to get sentiment from the entire Ganjar dataset. Meanwhile, the combination model was used to get sentiment for all candidate datasets.

Furthermore, the sentiment results obtained from each model were compared with each other. In this case, the tweets that mention the three characters are taken so that we can compare the accuracy of each model in determining the sentiment for the individual entities in the tweet, rather than a single sentiment for the entire tweet.

There are 607 tweets mentioning the three figures. After cleaning the duplicate tweets, 444 tweets were obtained. By comparing the overall sentiment results of each model, we find that the combined model will always produce the same result for all candidates. Meanwhile, the model that is created for a specific candidate may get different results, depending on the candidate being analyzed. Comparison of sentiment tweet results obtained from the specific candidate model and combination model is presented in Table 3.

As we can see from Table 3, example Tweet 5 has a positive sentiment towards Anies, represented by the sentence "*Elektabilitas Anies Melejit, Lampaui Prabowo dan Ganjar"*. And when the specific model for Anies used to predict the sentiment of the tweet, the model succeeds in classifying the tweet as positive sentiment. Otherwise, when the specific model for Ganjar and Prabowo used to predict the sentiment for each candidate, the model can classify tweet as negative. Meanwhile, when combination model used to classify the tweet, the model predicts the tweet for all entity as negative.

In example Tweet number 1, Ganjar received positive sentiment, as shown in the sentence *"Pak @ganjarpranowo ungguli @aniesbaswedan dan @prabowo Jika head to head."*. Model for Ganjar succeeds in classifying the tweet as positive sentiment. Model for Anies can also predict the sentiment for Anies as negative. Even so, the model for Prabowo predicts Prabowo's entity sentiment incorrectly, which classifies the tweet as positive.

Table 3. Model comparison

		Naïve Bayes	SVM	Random Forest	Neural Networks
Prabowo	Accuracy	70.17%	75.68%	87.89%	87.39%
	Precision	74.88%	80.10%	93.38%	90.58%
	Recall	66.60%	70.87%	84.04%	85.96%
	F1 Score	70.50%	75.20%	**88.47%**	88.21%
Ganjar	Accuracy	69.37%	74.77%	87.39%	87.29%
	Precision	69.22%	72.84%	83.28%	83.44%
	Recall	84.22%	89.73%	97.53%	96.77%
	F1 Score	75.99%	80.41%	**89.84%**	89.61%
Anies	Accuracy	65.47%	66.67%	81.48%	81.58%
	Precision	70.13%	74.14%	89.14%	88.41%
	Recall	67.56%	67.54%	78.05%	80.00%
	F1 Score	68.82%	70.68%	83.22%	**83.99%**
Combination	Accuracy	61.69%	62.95%	81.59%	81.76%
	Precision	68.19%	67.53%	88.29%	88.04%
	Recall	65.40%	68.61%	81.30%	81.60%
	F1 Score	66.77%	68.07%	84.65%	**84.70%**

Table 4. Comparison of tweet sentiment from specific candidate model and combination model

No	Tweet	Specific Candidate Model			Combination Model		
		Anies	Prabowo	Ganjar	Anies	Prabowo	Ganjar
1	Pak @ganjarpranowo ungguli @aniesbaswedan dan @prabowo Jika head to head. Ini belum kampanye dan belum di capreskan oleh PDI loh. Bayangkan jika sdh dicapreskan & mesin partai bergerak, dijamin hanya satu putaran	Negative	Positive	Positive	Negative	Negative	Negative
2	Setahun terakhir, Ganjar Pranowo dan juga Ridwan Kamil mendapat surplus dukungan pemilih mula. Sebaliknya, Prabowo Subianto dan Anies Baswedan mengalami defisit dukungan. #Survei #AdadiKompas	Negative	Positive	Positive	Positive	Positive	Positive
3	Lainnya masih pegang kalkulator, pak @prabowo sudah berangkat duluan. Colek Pak @aniesbaswedan dan Pak @ganjarpranowo ... Smoga pesta demokrasi 2024 berjalan dengan damai. Aamiin YRA.	Positive	Positive	Neutral	Positive	Positive	Positive
4	Elektabilitas Ganjar Pranowo Unggul di Survei PRC, Disusul Anies Baswedan dan Prabowo Subianto	Positive	Negative	Positive	Positive	Positive	Positive
5	Efek Formula E? Elektabilitas Anies Melejit, Lampaui Prabowo dan Ganjar https://t.co/FX4vUmmusC #AniesBaswedan #FormulaE #GanjarPranowo #headline	Positive	Neutral	Negative	Negative	Negative	Negative
6	Kl Ganjar dan Prabowo jd satu kelar kontestan lain. Gubernur Jawa Tengah Ganjar Pranowo unggul dengan angka 30,3% disusul Menteri Pertahanan Prabowo Subianto 27,3% dan Gubernur DKI Anies Baswedan 22,6%.	Neutral	Positive	Positive	Positive	Positive	Positive
7	Berbeda pendapat atau pilihan, boleh,tetapi jangan saling menghina. @prabowo @aniesbaswedan @ganjar_pranowo @ridwankamil @sby.yudhoyono @agusyudhoyono @sandiuno @pk_sejahtera #SahabatRK #SahabatRidwanKamil #RelawanSahabatRK #pplhiupdate_2020 #pplhiupdate_2016 #IndonesiaJuara	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
8	LSP merilis survei elektabilitas capres 2024. Prabowo Subianto memiliki elektabilitas tertinggi disusul Anies Baswedan dan Ganjar Pranowo.	Negative	Positive	Negative	Positive	Positive	Positive

3.3 Twitter Sentiment

Based on a comparison of the sentiment results from the specific candidate model and the combination model for all candidates, we found that the specific candidate model has a better ability in determining the sentiment for the individual entities in the tweet. Therefore, the tweet sentiment results that we present were obtained from sentiment analysis using specific candidate model.

Table 5 and Figure 5 present the sentiment result from each candidate. From the sentiment analysis result, the highest sentiment towards Prabowo is neutral (55.49%), the highest sentiment towards Ganjar is positive (61.34%), and the highest sentiment towards Anies is neutral (44.84%). Furthermore, when sentiment towards the three candidates compared together, it can be seen in Table 6 that Anies was the presidential candidate who received more negative sentiment than the other two (56.63%). Meanwhile, Ganjar Pranowo got the most positive sentiment of all (42,69%). For the neutral sentiment, Anies Baswedan also got the most results (39.87%), followed by Prabowo (38.99%) and Ganjar Pranowo (21.14%).

Table 5. Sentiment analysis result for each candidate

	Prabowo	Ganjar	Anies
Positive	39.17%	61.34%	38.26%
Negative	5.34%	10.38%	16.90%
Neutral	55.49%	28.28%	44.84%
Total	100%	100%	100%

Table 6. Comparison of positive, negative, and neutral sentiment from all candidates

	Positive	Negative	Neutral
Prabowo	25.63%	14.13%	38.99%
Ganjar	42.69%	29.24%	21.14%
Anies	31.68%	56.63%	39.87%
Total	100%	100%	100%

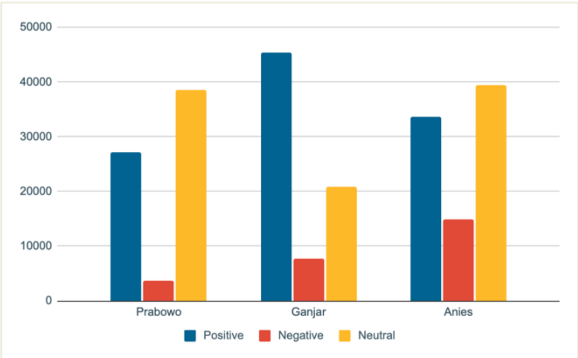

Figure 5. Sentiment results towards Prabowo, Ganjar Pranowo, and Anies Baswedan

Figures 6, 7, and 8 present the sentiment for each candidate over time since January until October 2022. From the line chart, the number of tweets discussing each candidate has increased every month.

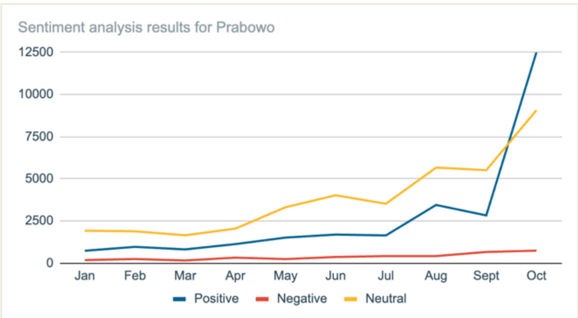

Figure 6. Sentiment analysis results for Prabowo

Line diagram on Figure 6 shows that tweets discussing Prabowo from January until September 2022 were mostly neutral rather than positive or negative. However, in October, the number of positive sentiments increased quite significantly and exceeded the neutral sentiment which was previously higher.

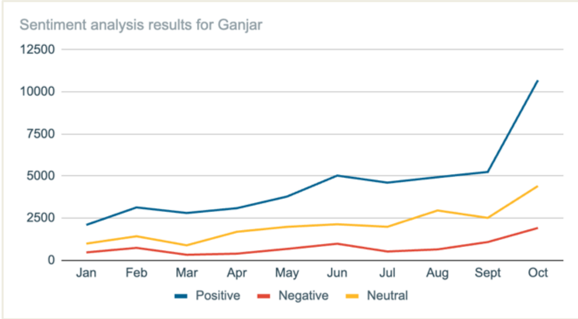

Figure 7. Sentiment analysis results for Ganjar

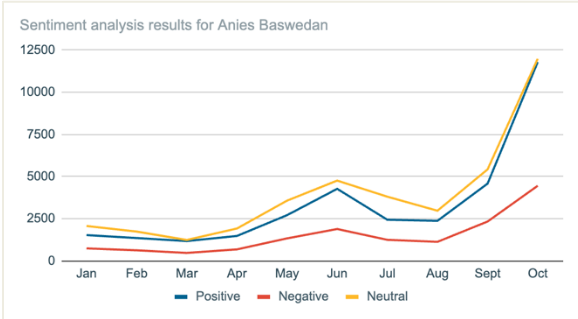

Figure 8. Sentiment analysis results for Anies

From the line diagram of Ganjar presented in Figure 7, positive sentiment towards Ganjar is always higher than negative or neutral from time to time. Meanwhile, on the line diagram of Anies presented in Figure 8, the neutral and positive sentiment seems to have a slight difference in result for each month. Moreover, they appear to have an overlap on March and October.

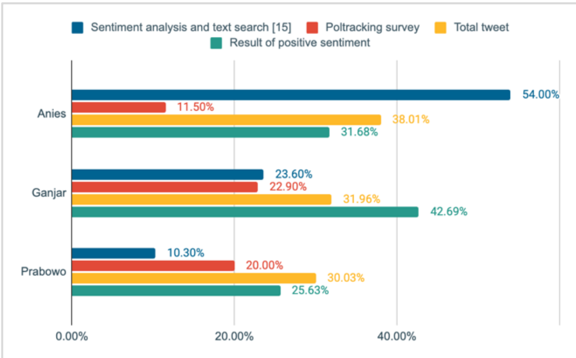

Figure 9 Comparison of total tweet and positive sentiment result with sentiment analysis from [15] and Poltracking survey

Figure 9 shows the comparison of total tweets and positive sentiment result with sentiment analysis result from Baharuddin et.al [15] and Poltracking survey. The result of Baharuddin et.al sentiment analysis is in accordance with data from Poltracking, which predict three strong names to run as presidential candidates in 2024 elections, although the significance of the three has a different percentage. Baharuddin et.al use text search to predict the strong candidates. Based on result of the total tweets obtained in this research, the significance of the three names also in accordance with

Baharruddin et.al result, which are sequentially occupied by Anies Baswedan (38.01%), Ganjar Pranowo (31.96%), and Prabowo Subianto (30.03%). On the other hand, the top positive sentiment results are in accordance with the Poltracking survey results, where Ganjar Pranowo is superior to the other candidates.

4. Conclusions

The purpose of our research is to conduct a sentiment analysis towards candidates of the 2024 presidential election in Indonesia. This research compares four machine learning methods and used k-fold cross-validation to perform model evaluation and obtained the best model for each dataset. 5000 tweet data from each candidate were used as a dataset to build and evaluate the model. The best model was then used to conduct the sentiment analysis for real data that collected from Twitter from January to October 2022. In summary, our research shows that the number of tweets discussing each candidate has increased every month since January until October 2022. Result of data collection shows that Anies Baswedan being the most discussed candidate on Twitter during January until October 2022. Even so, he has the most negative sentiment compared to the other two candidates. Our results also show that Ganjar Pranowo was the presidential candidate who received the most positive sentiment, followed by Anies Baswedan and Prabowo. Furthermore, even though Prabowo was the least tweeted about, the sentiment regarding him is mostly neutral and the positive sentiment seems to be increasing in every month. We also discover that Random Forest and Neural Networks have the best performance in conducting sentiment analysis. Each of the algorithms has an average accuracy calculation of 84.59% and 86.55%, and an average f1-score of 84.51% and 86.63%. Lastly, we also found that using a model for each candidate or entity in determining the sentiment of a tweet can provide better results rather than using a combined model. Specific model for each entity can provide sentiment results that are specific to the candidate being analyzed, rather than sentiment for the tweet as a whole. Our work is certainly having some limitations. First, the number of datasets that we used to construct and evaluate the model was only 15.000 tweets (5.000 tweets for each candidate). That number was very minimum when compared to the total tweets obtained, which was only 6.48% of a total of 231.514 tweets. Second, our datasets also experience class imbalance issues, a condition when the proportion of the class label from the datasets is not balanced. From all datasets, the proportion of negative class labels was very small compared to positive and neutral class labels, which is only 15.93%. The occurrence of this class imbalance can cause the model to produce low precision and recall when evaluated on a rare class. Third, we found from the manual annotation process that the crawling result for Prabowo did not only obtain tweets discussing Prabowo Subianto, one of the political figures that referred to be a presidential candidate. The results of data collection also found other similar names which were widely discussed by Indonesian netizens on Twitter like Kapolri Listyo Sigit Prabowo and Edhy Prabowo. Therefore, a further filtering process is needed to obtain a tweet data set that is appropriate to the topic being discussed. Fourth, our research only used Twitter data to collect sentiment from Indonesia’s citizens. Twitter is only one of many social media that is popular in Indonesia. There is still a lot of information related to Indonesia’s citizen preferences that can be found on other social media besides Twitter. For further research, researcher can also use data from other social media like Instagram, Facebook, and TikTok. Another limitation of this research is the time used. This research only use data from January until October 2022 to analyze the public sentiment of Indonesia's 2024 presidential election candidate. There is still a possibility that the sentiment result towards each candidate would be different when similar research conducted in the time close to the presidential election. It is recommended that further research can collect and analyze similar data periodically until the election period. Another recommendation for future research is to not only used data from Twitter but also from other social media that is widely used by the citizens. Using more data will capture more sentiment. By using more data from several social media, researchers can also know which social media has the most discussion on topics surrounding the presidential election. For future research, researcher can also conduct sentiment analysis for the presidential election long before the election until the election being held to get the broad picture of sentiment development from time to time. Furthermore, to deal with class imbalance problem, future researchers may also try to use data balancing technique like random under sampling, random over sampling, or Synthetic Minority Over-sampling Technique (SMOTE). We also recommend future researchers to use other machine learning methods that are not widely used for sentiment analysis to evaluate the performance of the algorithm in conducting text analysis work.

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