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Comparison Of Classification Methods On Sentiment Analysis Of Political Figure Electability Based On Public Comments On Online News Media Sites

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Abstract. Elections are an important part of the political process so that not a few figures from political parties begin preparing to participate in the process. Electability is one of the issues of concern, various things are done to be able to increase the electability of political figures who participated in the general election. Media has become one of the important tools used to increase electability, one of which is online news media. News coverage in online news media with its real-time nature will very quickly get comments from readers and can be used as an assessment of political figures in the form of sentiment analysis. However, it is not easy to analyze sentiments from various comments on online news media, because comments that contain text have irregularities, especially in Indonesian texts. Text mining is one way that can be used to overcome this. Pre-processing of text in text mining is an important part of getting basic information contained in comments. This study uses the Indonesian text pre-processing using the Gata text-mining framework. Then proceed with extracting more in-depth information using the Naïve Bayes classification method and Support Vector Machine which is optimized using Particle Swarm Optimization. The tests carried out with both methods get the results that, the Particle Swarm Optimization based Support Vector Machine method is the best method in the process of classifying sentiments analysis of political figures with an accuracy of 78.40% and AUC 0.850. The results of this study get an effective algorithm in classifying positive and negative comments related to political figures from online news media.

1. Introduction

Elections are an important part of the political process so in Indonesia. being a general election in Indonesia in 2019, not a few political figures begin to get ready to participate in the process. Various attempts by political leaders were made to increase their electability. Electability is full of popularity, a popular person will have high electability [1]. In politics, the role of electability is always challenging to convince voters to choose the political figure they like [2]. The tendency of electability is the most during the election season political compilation is not popular with general elections [2] and can be a benchmark for measuring one's level of electability [1].

Sentiment analysis is a process of comparison to uncover and categorize opinions expressed in text, to determine whether responses to a particular topic are positive, negative, or neutral [3][4]. Sentiment analysis also called mining is a field of study that analyzes opinions, sentiments, opinions, judgments, and emotional judgments on attribute entities discussed in a paper [5]. Analyzing sentiments in political texts can be a representation of election results, the electability of candidates, or real political

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representation in the State [3]. Related to web technology, followed by political activity in online media is an aspect that is a consideration to analyze the sentiments of the electability of political figures through written posts and comments. Research related to sentiment analysis of political figures originating from online media is mostly done by researchers with various methods used [6][7][8][9]. Conducting sentiment analysis originating from text posting and commenting on online media is not easy, because comments that contain text have irregularities, depending on Indonesian texts that have distinctive features from other languages [10].

This study applies machine learning technology to analyze electability sentiments of political figures originating from comment text data on online news media in Indonesia. Text mining is one method used to extract unstructured information from combining text data [11], which is converted into a numerical value that will be used in various data mining methods [12]. In addition to using the text-mining method, data mining methods with group functions are also used for text data that has been extracted with the aim of getting complete information. The Naïve Bayes algorithm [13] and Support Vector Machine [14] optimized with Particle Swarm Optimization [15] are data mining methods for the classification used in this study.

The main purpose of this research is to learn and get the best and decisive method in classifying and analyzing sentiments. Analysis of reader comments on online news media on the electability of political figures seeking the electoral process. This research is also expected to provide solutions in terms of the sentiment classification analysis of political figures and support the discussion of further research on other research objects, such as sentiment analysis in the level of customer satisfaction in the company.

There are several previous studies that used a Naïve Bayes and Support Vector Machine classification model, including:

- 1. Conducted a sentiment analysis of the 2017 DKI Jakarta Governor Election which was widely discussed in cyberspace, especially on Twitter social media. The method used in this study, for data preprocessing using tokenization, cleansing, and filtering, to determine the sentiment class with the Lexicon Based method. The classification process uses the Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM) methods [16].
- 2. Conducted a study on the analysis of President Jokowi's data sentiments with preprocessing, normalization and stemming using the Naïve Bayes and SVM methods. Search techniques in this study use Boolean searching with the operator "AND". The data that has been obtained is labeled positive, neutral and negative by the researcher then corrected by linguists. After that, preprocessing is done, either changing the word is not standard into standard or commonly called normalization using a dictionary and search for the root word, stemming with the help of the Literary Master application. Furthermore, it is also done tokenization of N-Gram, Unigram, Bigram, and Trigram against the sentence, then removes the commonly used words and does not have valuable information in a context or commonly called stopword removal, and retains emoticons because emoticons are symbols that show expression someone into writing [6].
- 3. Conducted a sentiment analysis study on the 2017 DKI Jakarta Governor Election with a predictive and descriptive approach. The main objective of this research is to analyze the sentiments of the 2017 DKI Jakarta Governor election on Twitter social media with a predictive and descriptive approach. Data is collected from Twitter using each candidate's username as a search query. For predictive approaches, machine learning algorithms such as the Naïve Bayes Multinomial and Support Vector Machine are used to classify datasets. While the descriptive approach, Time Series Graph and Word Clouds are used to gain deeper insights and find a link between Twitter sentiment and the results of the election itself [17].

2. Methods

Research on the comparison of classification methods in the analysis of Indonesian social media sentiment related to the election of the governor of DKI Jakarta. Sentiment analysis has challenges such as comments usually ambiguous, language barrier problems, harsh words, excessive comments, and sentiment clauses. This research tries to distinguish the issue of sentiment classification from Indonesian

social media regarding governor elections in DKI Jakarta. Several steps are taken to overcome the problem that includes preprocessing. Preprocessed sentiments are then grouped into positive, negative, and neutral. The classification methods used in this study are the Summation Method, Average on Tweet, Average on Tweet with the threshold on objective scores, Weighted Average, and Naïve Bayes. The experimental results show that Naïve Bayes produces high precision values, high recall values and high accuracy values for neutral and positive sentiments, but Naïve Bayes does not produce good results for negative sentiments [18]. Research on comparative orientation analysis using the technique of Support Vector Machine and Naïve Bayes on film user reviews. Sentiment analysis is used to recognize and know the users' responses to a film. Data is collected through user movie reviews online in the Internet Movie Database archive. Data processing is done by using RapidMiner Tools. The results of the evaluation of Support Vector Machine and Naïve Bayes algorithms in the movie user review dataset, it is shown that drama films have a high degree of accuracy among other film genres. The evaluation results show that Support Vector Machine techniques have the best accuracy than Naïve Bayes [19].

3. Results And Discussion

In this study using the Cross-industry standard process for data mining, known as CRISP-DM method, the CRISP-DM stages in Figure 1 [20], above are as follows:



Figure 1. Method of CRISP Data Mining. Figure was adopted from Kenneth Jensen, 2016.

3.1 Business Understanding

At the business understanding stage, an understanding of the object of research is carried out. Understanding of the object of research is done by digging up information through several online news media sites on the object of research. Motivation in this phase is that the news presented is usually in the form of text on digital media which is grouped based on the contents of the discussion of each news category. Online media is not only limited as a medium for reading news articles but can also be used to see the issues that occur and can even be used to see the electability of a political figure. This sentiment analysis is done to find classification methods that can help determine positive and negative news article comments. At this stage, an understanding is also made to find the best classification method so that it can help during the data processing process which will be done by comparing the results of the

algorithms used and to improve the performance of the classification method can be done by using feature selection.

3.2 Data Understanding

At the data understanding stage, the process of retrieving raw data is carried out in accordance with the required attributes. Data obtained from news media sites online www.detik.com, www.tribunnews.com, www.kompas.com, www.merdeka.com, www.viva.co.id and www.kompasiana.com. The data were collected from February 16, 2018, until May 31, 2018. The primary data obtained were 1480 commentary data from news articles on online news media, namely Detiknews with 1393 comments data, Tribunnews with 8 comment data, Kompas with 72 comment data, Merdeka with 3 comment data, Viva with 3 comment data and Kompasiana with 1 comment data. After the data is collected then the cleansing process is carried out, obtained 1459 comments data. This study uses comment data in Bahasa (Indonesian language).

3.3 Data Preparation

The data preparation stage is a stage with a data preparation process that aims to obtain clean data and is ready for use in research. In the early stages of text mining, the text preprocessing stage will be performed, at this stage, researchers will use the Tools Gata Framework Textmining. The following are the steps taken in the text preprocessing.

3.3.1 Case Folding

Not all text documents are consistent in using capital letters. Therefore, the role of Case Fold is needed in converting all text in a document into a standard form (usually lowercase or lowercase letters), as shown in table 1.

Before	After
"DARIMANA LOGIKANYA SI AHY	"darimana logikanya si ahy paling cucok
PALING CUCOK DAN	dan elektabilitas tinggi utk cawapres
ELEKTABILITAS TINGGI UTK	jokowi anak masih hijau dan tidak
CAWAPRES JOKOWI ANAK	punya pengalaman politik dan eksekutif
MASIH HIJAU DAN TIDAK PUNYA	nol besar !!! ngaco!!!
PENGALAMAN POLITIK DAN	#2019tetapjokowi"
EKSEKUTIF NOL BESAR !!!	
NGACO!!! #2019TETAPJOKOWI"	

 Table 1. Comparison of Text Before and After the Case Folding Process

3.3.2 Tokenizing

The Tokenizing step is the step of cutting the input string based on each word that composes it, as seen in table 2.

Table 2. Comparison of Texts Before and After the Tokenizing Process

Before	After
"darimana logikanya si ahy paling	"darimana logikanya si ahy paling
cucok dan elektabilitas tinggi utk	cucok dan elektabilitas tinggi utk
cawapres jokowi anak masih hijau dan	cawapres jokowi anak masih hijau dan
tidak punya pengalaman politik dan	tidak punya pengalaman politik dan
eksekutif nol besar !!! ngaco!!!	eksekutif nol besar !!! ngaco!!!
#2019tetapjokowi"	#2019tetapjokowi"

3.3.3 Tagging

Eliminate the mention of the user name mentioned (@username), delete hashtag (#hastag), delete punctuation, delete numbers because only text data is used, delete links (http: //), delete special characters such as symbols or emoticons, omit words foreign words because they only take words that speak Indonesian. For the word ahead, the word "no" will be normalized by using the underscore "_" to have a clear meaning, for example, "not good" to "not_good" because the word "no" is negative while the word "good" is positive. the results of the tagging process can be seen as in table 3.

Table 3. Comparison of Texts Before and After the Tagging Process

Before	After
"darimana logikanya si ahy paling	"darimana logikanya si ahy paling
cucok dan elektabilitas tinggi utk	cucok dan elektabilitas tinggi utk
cawapres jokowi anak masih hijau	cawapres Jokowi anak masih hijau
dan tidak punya pengalaman politik	dan tidak_punya pengalaman politik
dan eksekutif nol besar !!! ngaco!!!	dan eksekutif nol besar ngaco"
#2019tetapjokowi"	

3.3.4 Filtering

Filtering Stage is the stage of taking important words from the token results. Can use a stoplist algorithm (throwing less important words) or wordlist (save important words). At this stage for slang words (in Indonesian) must be normalized into the standard form, for example, "to" be "for". The results of the filtering process can be seen in table 4.

Table 4. Comparison of Texts Before and After the Filtering Process

Before	After
"darimana logikanya si ahy paling	"darimana logikanya si ahy cocok
cucok dan elektabilitas tinggi utk	elektabilitas cawapres Jokowi hijau
cawapres Jokowi anak masih hijau dan	tidak_punya pengalaman politik
tidak_punya pengalaman politik dan	eksekutif nol ngaco"
eksekutif nol besar ngaco"	

3.3.5 Stemming

The stemming process is the process of finding the root of the word resulting from the filtering process. The root search for a word or commonly referred to as a basic word can reduce index results without having to eliminate meaning. The results of the stemming process can be seen in table 5.

Table 5. Comparison of Texts Before and After the Stemming Process

Before	After
"darimana logikanya si ahy cocok	"darimana logika si ahy cocok
elektabilitas cawapres Jokowi hijau	elektabilitas cawapres Jokowi hijau
tidak_punya pengalaman politik	tidak_punya pengalaman politik
eksekutif nol ngaco"	eksekutif nol ngaco"

The data preparation process uses the Gata Framework Textmining pre-processing tool, as shown in figure 2.

	🛗 Text Mining					5	ablu, 23 Februari 2019	LOGIN -
			ic	Upload Excell 2003		Web Service (URL)		
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No	Teks	@Anotation Removal	Transformation: Remove URL	Transformation: Not (Negative) Tokenization: Regexp	Normalization: Indonesian Slank	Indonesian Stop word removal	Indonesian Stemming
1	DARIMANA LOGIKANYA SI AHY PALING CUCOK DAN ELEKTABILITAS TINGG UTC CAWAPRES JOKOW. ANAK MASIH HIJAU DAN TIDAK PUNYA PENGALAMAN POLITIK DAN EKSEKUTIF NOL BESAR III NGACOIII #2019TETAPJOKOWI	darimana logikanya si ahy paling cucok dan elektabilitas tinggi utk cawapres jokowi. anak masih higa udan tidak punya pengalaman politik dan eksekutif nol besar 11 ngaco11 #2019tetapjokowi	darimana logikanya si ahy paling cucok dan elektabilitas Inggi utk cawapres jokowi. anak masih hijau dan tidak punya pengalaman politik dan eksekutif nol besar ili ngaco!! #2019tetapjokowi	darimana logikanya si ahy paling cucok dan elektabilitas tingd utk cawapres jokowi anak masih hijau dan tidak_punya pengalaman politik dan eksekuti nol besar til ngaco!! #2019tetapjokowi	darimana logikanya si ahy paling cucok dan elektabilitas tinggi utk cawapres jokowi anak masih hijau dan tidakpunya pengalaman politik dan eksekutif nol besar ngaco tetapjokowi	darimana logikanya si ahy paling cakep dan elektabilitas tinggi utk cawapres jokowi anak masih hijau dan tidakpunya pengalaman politik dan eksekutit nol besar ngaco tetapjokowi	darimana logikanya si ahy cakep elektabilitas cawapres jokowi anak hijau tidakpunya pengalaman politik eksekutif nol ngaco tetapjokowi	darimana logika s ahy cakep elektabilitas cawapres jokowi anak hijau tidakpunya alam politik eksekutif n ngaco tetapjokow

Figure 2. Gata Framework Textmining. http://www.gataframework.com/textmining/

3.4 Modelling

Is the mining technique selection phase by determining the algorithm to be used. The tool used is RapidMiner version 8.2. The model test results are classifying positive news articles and negative news articles using the Naive Bayes and Naive Bayes algorithm based on Particle Swarm Optimization (PSO) and Support Vector Machine and Support Vector Machine based on Particle Swarm Optimization (PSO) to get the best accuracy value. In Figure 3 the design of the RapidMiner model is used.



Figure 3. Model Design Comparison of Support Vector Machine and Naïve Bayes Algorithms Figure 4 below is a design of the RapidMiner model for the Naive Bayes algorithm based on Particle Swarm Optimization (PSO) and Support Vector Machine based on Particle Swarm Optimization (PSO).



Figure 4. Model Design Comparison of Support Vector Machine based PSO Algorithms and Naïve Bayes based PSO

3.5 Evaluation

The evaluation phase aims to determine the usefulness of the model that has been successfully made in the previous step. For evaluation, 10-fold cross-validation is used. Following is the design of the Support Vector Machine algorithm model testing process used.



Figure 5. Design of a 10-Fold Cross Validation Process for Support Vector Machine



Figure 6. Design of a 10-Fold Cross Validation Process for Naïve Bayes

Figure 5 and figure 6 describes the design process in the operator's Support Vector Machine and Naïve Bayes cross-validation in Figure 4. In this test, the data used is clean data that has passed the preprocessing text stage. Data is taken from the Read Excel operator, this is done because the dataset is stored in Excel (.xls). Process documents from files to convert files to documents. The validation process consists of training data and test data. Subprocess training is used to train the model. The trained model is then applied to subprocess testing. Furthermore, after the data has been tested, a cross-process has been carried out where the test data is then used as training data or vice versa, the previous training data used is now the testing data. This process is repeated 10 times for each part so that the parts of the ten parts have been testing data for the Naive Bayes algorithm and Support Vector Machine. At this stage also uses the Role Set which functions to determine the fields in the class then use Particle Swarm Optimization (PSO) so that the resulting accuracy is higher than the results of the previous modeling. Classification. 3). 0.70 - 0.80 = fair classification.4). 0.60 - 0.70 = poor classification. 5). 0.50 - 0.60 = failure. As for the comparison of the accuracy and Area Under Curve (AUC) results of the two algorithms that have been used can be seen in table 6.

[a]	ble	6.	Com	parison	of	Accuracy	and	AUC
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Algorithms	Accuracy	AUC
Support Vector Machine	76.09%	0.848
Support Vector Machine + PSO	78.40%	0.850
Naïve Bayes	68.21%	0.672
Naïve Bayes + PSO	74.98%	0.708

3.6 Deployment

At the deployment stage, application design will be carried out using data sets on data sets about the electability of political figures. This stage is done by creating a tool built with the VB.net programming language and MySQL database. Figure 7 shows the main menu page for the analysis of sentiments from the selection of political figures.



Figure 7. Display of the Main Menu Application

Figure 8 shows a data dictionary page from the calculation of the Naive Bayes model and Support Vector Machine,

		Masukkan Kalimat	: Anda		
in	donesia buti	ah pemimpin mu	ıda		Pencarian Bobot
	КАТА	Bobot Kata SVM	NB (Positive)	NB (Negative)	
•	indonesia	0.0264376184	0.0205500129	0.0095791630	
	butuh	-0.0132533109	0.0012375048	0.0067257636	
	pemimpin	0	0	0	
	muda	0.0200988015	0.0187727949	0.0096465361	
					hapus Data
				Kesimpu	ılan Prediksi
Гot	al Bobot SVM	0.03328	Komenta	Kesimpu rnya Positif	ılan Prediksi
Tot Tot	al Bobot SVM al Bobot NB	0.03328	Komenta Komenta	Kesimpu rnya Positif rnya Positif	ulan Prediksi
Fot	al Bobot SVM al Bobot NB << Kemb	0.03328 0.01460 ali Ke Menu Uta	Komenta Komenta uma	Kesimpu rnya Positif rnya Positif Copyright	ılan Prediksi :@2018 Nuri (AF)

Figure 8. Display Sentence Check Menu

Figure 9 display of the Data Dictionary Menu

Load Excel Import Data EXcel	Cara Import Data Excel di VB.net 1. Simpan File dengan extension x8x 2. Buat sheet dengan nama svm_bobot 3. buat 3. obumn dengan nama§/n.ema , bobot)
Load Excel Import Data EXcel	Cara Import Data Excel di VB.net 1. Simpan File dengan extension x8x 2. Buat sheet dengan nama svm_bobot 3. buat 3 oblums dengan namadi, nama . bobot
Load Excel Import Data EXcel	Cara Import Data Excel di VB net 1. Simpan File dengan extension xtax 2. Buat sheet dengan nama svm. jobbot 3. buat 3 columna dengan namajdi. nama , bobot
Excel Import Data EXcel	Cara Import Data Excel di VB.net 1. Sinpan File dengan extension xisx 2. Buat sheet dengan nama sim_bobot 3. buat 3 columna dengan namajid, nama , bobot
Import Data EXcel	Cara Import Data Excel di VB.net 1. Simpan File dengan extension x/sx 2. Buat sheet dengan nama svm_bobot 3. buat 3 columns dengan nama(id, nama , bobot
Import Data EXcel	Cara Import Data Excel di VB.net 1. Simpan File dengan extension x/sx 2. Buat sheet dengan nama svm_bobot 3. buat 3 columns dengan nama(id, nama , bobot)
Import Data EXcel	Simpan File dengan extension xlsx Buat sheet dengan nama svm_bobot Suat 3 columns dengan nama(d, nama , bobot)
Import Data EXcel	2. Buat sheet dengan nama svm_bobot 3. buat 3 columns dengan nama(id, nama , bobot
Data EXcel	 Buat sheet dengan nama svm_bobot buat 3 columns dengan nama(id, nama , bobot)
EXcel	3. buat 3 columns dengan nama(id, nama , bobot
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							buat PredikSl
		Result D	ata Excel		D		
Nomor	Comment	Result D	status	Bobot SVM	Prediksi SVM	Bobot NB	Prediksi NB
Nomor 1	Comment saatnya pemimpir	n muda	Status positif	Bobot SVM 0.0200988015	Prediksi SVM SVM-Positif	Bobot NB 0.009126258	Prediksi NB 7 NB-Positif
 Nomor 1 2	Comment saatnya pemimpin pilgub aja gagal	n muda	Status positif negatif	Bobot SVM 0.0200988015 -0.099365163	Prediksi SVM SVM-Positif SVM-Negatif	Bobot NB 0.009126258 -0.044235784	Prediksi NB 7 NB-Positif 4 NB-Negatif
Nomor 1 2 3	Comment saatnya pemimpin pilgub aja gagal maju terus	n muda	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.044235784 0.066477103	Prediksi NB 7 NB-Positif 4 NB-Negatif 5 NB-Positif
Nomor 1 2 3	Comment saatnya pemimpir pilgub aja gagal maju terus	n muda	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.04423578- 0.066477103	Prediksi NB 7 NB-Positif 4 NB-Negatif 5 NB-Positif
Nomor 1 2 3	Comment saatnya pemimpir pilgub aja gagal maju terus	n muda	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.044235784 0.066477103	Prediksi NB 17 NB-Positif 4 NB-Negatif 15 NB-Positif
Nomor 1 2 3	Comment saatnya pemimpin pilgub aja gagal maju terus	a muda	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.044235784 0.066477103	Prediksi NB 17 NB-Positif 4 NB-Negatif 15 NB-Positif
Nomor 1 2 3	Comment saatnya pemimpin pilgub aja gagal maju terus	1 muda	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.04423578- 0.066477103	Prediksi NB 17 NB-Positif 4 NB-Negatif 15 NB-Positif
Nomor 1 2 3	Comment saatnya pemimpir pilgub aja gagal maju terus << Kembali K	e Menu Utar	Status positif negatif positif	Bobot SVM 0.0200988015 0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.04423578 0.066477103	Prediksi NB 17 NB-Positif 4 NB-Negatif 5 NB-Positif AF)
Nomor 1 2 3	Comment saatnya pemimpir pilgub aja gagal maju terus	e Menu Utar	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Negatif SVM-Positif	Bobot NB 0.009126258 -0.04423578 0.066477103	AF)
Nomor 1 2 3	Comment saatnya pemimpin pilgub aja gagal maju terus << Kembali Ke	e Menu Utar	Status positif negatif positif	Bobot SVM 0.0200988015 -0.099365163 0.1098153986	Prediksi SVM SVM-Positif SVM-Positif SVM-Positif	Bobot NB 0.009126258 -0.04423578- 0.066477103	AF)

Figure 9. Display of the Data Dictionary Menu Figure 10 is a page view of the sentence check menu.

Figure 10. Sentences Check Menu Display in Excel

This page is a page to check every sentence that is inputted freely and to know the sentence weight and status prediction of the inputted sentence. Figure 18 is a page view of the sentence check menu in an Excel file. This page is a page to check every sentence contained in an Excel file. Difference between sentence check menus in Excel with sentence check menu is if you use sentence check menu in Excel, the sentence that will be checked can be in large numbers, but if you use sentence check menu, only one sentence can be checked.

4. Conclusion

From the results of the research that has been conducted related to the classification of electability sentiment analysis of political figures on online news media comments, it can be concluded that the use of the Gata Textmining framework is very helpful in the commentary pre-processing of Indonesian. The use of Support Vector Machine Algorithm based on Particle Swarm Optimization (PSO) has a better level of accuracy than Naive Bayes based on Particle Swarm Optimization (PSO). While Particle Swarm Optimization (PSO) plays an important role in increasing the accuracy of the Support Vector Machine algorithm based on Particle Swarm Optimization (PSO) can be a solution for classification in the sentiment of analysis of political figures. Based on the results above, this study also carried out a deployment phase based on the accuracy of the algorithm Support Vector Machine based on Particle Swarm Optimization (PSO).

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